CONVERGENCE IN GLOBAL CAPITAL MARKETS

A Dissertation
Presented to
The Academic Faculty

by

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In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy in the
College of Management

Georgia Institute of Technology
August 2006

CONVERGENCE IN GLOBAL CAPITAL MARKETS

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To My Family

ACKNOWLEDGEMENTS

I would like to thank my advisor, Prof. Cheol Eun for his guidance and support. I also thank the other committee members, Prof. Jayaraman, Prof. Chakrabarti, Prof. Clarke, and Prof. Kilic for their helpful comments on my dissertation. While I was away from the campus during my last year at Georgia Tech, Mr. Hyung Suk Choi helped me with administrative matters. I greatly appreciate his help and hope that he will have much progress in his research.

However, I owe most of all to my family, and, especially, to my wife, Yoonsook. Without her help and support, I could not have even dreamed of coming back to school to pursue a Ph.D. degree. Thus, I dedicate this work to my family (my mother and father, Yoonsook and two children, Jaewon and Jaebin).

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SUMMARY

In chapter 1, we show (i) that the risk-return characteristics of our sample of 17 developed stock markets of the world have converged significantly toward each other during our study period 1974 – 2004, and (ii) that this international convergence in risk-return characteristics is driven mainly by the declining 'country effect', rather than the rising 'industry effect', suggesting that the convergence is associated with international market integration. Specifically, we first compute the *risk-return distance* among international stock markets based on the Euclidean distance and find that the distance thus computed has been deceasing significantly over time, implying a mean-variance convergence. In particular, the average risk-return distance has decreased by about 43% over our sample period. The speed of convergence, however, varies greatly across individual markets, largely reflecting the initial distance of each individual market from the international average risk-return characteristic. Lastly, we document that the risk-return characteristics of our sample of 14 emerging markets have been converging rapidly toward those of developed markets in recent years. This development notwithstanding, emerging markets still remain as a distinct asset class.

In chapter 2, we examine the historical evolution of international earnings-to-price ratios for a sample of 17 markets over the period 1980 – 2004. We introduce a distance measure of earnings-to-price ratios among international stock markets and find that earnings-to-price ratios of 17 markets have significantly converged toward each other during the period. The average distance measure for 17 markets has decreased by about 80 percent during the period. The speed of convergence for individual markets

varies and mainly reflects the initial distance of individual markets from the international average. We also find that although both country and industry effects account for convergence in earnings-to-price ratios among the sample markets, country effect dominates industry effect in terms of the magnitude. We further examine what could explain the declining country effect and document that the time trend of dividend-yield distance measure closely follows that of earnings-to-price distance measure. This result suggests that convergence in earnings-to-price ratio is mainly due to convergence in economic factors such as growth opportunities or discount rates rather than due to convergence in accounting practices.

CHAPTER 1

MEAN-VARIANCE CONVERGENCE AROUND THE WORLD

Introduction

In the standard mean-variance analysis of a portfolio, three groups of parameters such as mean returns, variances of returns, and correlations among those returns, span the opportunity set, which an investor faces. For example, in his efficient set mathematics, Roll (1977) shows that these three groups of parameters jointly determine the shape of a mean-variance efficient portfolio[1].

As international capital markets are becoming more integrated, these three parameters for stock markets may start to behave in a more concerted manner. Longin and Solnik (1995), in fact, report that the average correlation of stock returns for seven major markets in their sample increased significantly over the period 1960–1990. They also find that the international correlation tends to rise when markets are volatile. King, Sentana, and Wadhwani (1994), on the other hand, examine sixteen developed stock markets during the period 1970-1988 and report that the average correlation among these markets increased around the 1987 global crash, but with no clear trend increase in the correlation. In a more recent study, Solnik and Roulet (2000) find that the average correlation of fifteen stock markets in their sample with the world market exhibits a weak positive trend, increasing from 66 percent in 1971 to 75 percent in 1998. While the exact magnitude of the increase in the international correlation depends on the study period and

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[1] See (A.9) through (A.11) in his efficient set mathematics.

the composition of sample markets, the overall weight of existing evidences indicates that the international stock market correlation has increased in recent years.

With deepening international market integration, not only the correlation structure but also the risk-return characteristics of stock markets may have evolved over time. As previously discussed, existing studies address the changing nature of international correlation, but not that of risk-return characteristics. This paper purports to fill this gap in the literature.

Specifically, the objectives of this paper are to (i) study the historical evolution of the risk-return characteristics of international stock markets and (ii) investigate what drives the documented pattern of evolution. In doing so, we compute the 'risk-return distance' as a way of quantifying the degree to which a market differs from the rest of sample markets in terms of risk-return characteristics. In particular, we measure the risk-return distance based on the Euclidean distance, which is a popular method for measuring the degree of (dis)similarity in cluster analysis. Since neither asset pricing models nor return-generating factors are used in computing the risk-return distance, our method is essentially model-free. Also, our Euclidean distance approach can easily accommodate multidimensional attributes of the observations. Once the risk-return distance is measured, we then proceed to examine if there are statistically significant time-trends in the distance measures. Our focus is on identifying particular evolutionary patterns in the risk-return characteristics of international stock markets if there is any. Our sample comprises 17 developed and 14 emerging stock markets for which we can obtain long enough return series necessary for our analysis.

The key findings of our paper can be summarized as follows. First, the risk-return characteristics of our sample of 17 developed stock markets have converged significantly toward each other during the period 1974 – 2004. Specifically, the average risk-return distance among these markets has decreased by about 43% over our sample period. As a result, these markets have become much less distinctive from each other in terms of risk-return characteristics. This international risk-return convergence is driven by the dual convergences in the risk and return dimensions. The risk-return convergence documented in this study remains robust to the inclusion of the varying market conditions. However, the risk-return characteristics of stock markets tend to diverge internationally when markets are volatile, *ceteris paribus*. We also show that the risk-return convergence and the increasing international correlation, an often cited trend, are related but distinct phenomena.

Second, the speed of convergence is found to vary greatly across individual markets. In particular, the speed of convergence is highest for Hong Kong, Austria, and Ireland, and lowest for Belgium, the Netherlands, and the United States, with the rest of sample markets falling in the middle. Notably, the speed of convergence is essentially zero for Belgium, implying that the country is at the focal point of international convergence. Furthermore, the speed of convergence is found to be closely related to the initial distance of each individual market from the international average risk-return characteristic: the farther away a market was initially, the more rapidly it has been converging toward the international average. It is noted that Japan is the only market that exhibits a tendency to 'diverge' from the rest of our sample markets. This Japanese exception may be attributable to the prolonged depression of the country's stock market throughout the 1990s, a period when many other countries experienced bullish market conditions.

Third, in order to identify the main driver for the risk-return convergence documented in this study, we investigate the separate effects of country vs. industry on stock market returns. We basically repeat the convergence tests using two 'decomposed' return series, one representing country effect and the other industry effect. We employ the Heston and Rouwenhorst (1994) method for the decomposition. Our test results clearly indicate that the risk-return convergence is driven by the decreasing country effect, rather than the rising industry effect, consistent with the view that the convergence is associated with international market integration. The risk-return characteristics attributable to industry effect exhibit no significant time trend, either upward or downward.

Fourth, the risk-return characteristics of our sample of 14 emerging markets have been converging rapidly toward those of developed markets in recent years. However, the average risk-return distance for emerging markets still remains much greater than that for developed markets. As of the end of our sample period, i.e., the second half of 2004, the average risk-return distance for our sample emerging markets is about three times as great as that for our sample developed markets. In fact, if both developed and emerging markets maintain their respective speeds of convergence in the future, our time trend projections suggest that a full convergence will not be reached until around year 2022. If the pace of convergence slows down as integration proceeds, a full convergence will take longer. Consequently, the recent convergence notwithstanding, emerging markets can be regarded as an effective vehicle for international diversification, consistent with the findings of Goetzmann, Li, and Rouwenhorst (2005) and others.

The rest of the paper is organized as follows. Section 2 describes the data and methodology. Section 3 provides tests of the mean-variance convergence among developed stock markets, whereas Section 4 investigates the driver of the mean-variance convergence documented in the previous section. Section 5 checks the robustness of the mean-variance convergence to the inclusion of the varying market conditions. In this section, we also briefly discuss the relationship between the increasing international correlation and the mean-variance convergence. Section 6 extends our analysis to a sample of emerging markets. Lastly, Section 7 offers summary and concluding remarks.

Data and Methodology

Data and Sample Selection

Our sample period for 17 developed markets spans January 1974 through December 2004. Our sample period starts in 1974 mainly because the process of capital market liberalization and integration began in earnest in the mid-1970s, following the collapse of the Bretton Woods system. With floating currency rates, countries face much reduced needs to control or regulate capital markets, launching the process of international financial integration. This process, in turn, might have changed the key characteristics of national stock markets over time. The 17 developed markets in our sample are: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Ireland, Italy, Japan, the Netherlands, Singapore, South Africa, Switzerland, the United Kingdom, and the United States. These are the markets for which the data on stock market returns are available from DataStream for the entire sample period. We employ weekly stock market returns in conducting our analysis.

We also collect the data on local industry returns for each of our sample developed markets. We use 10 broad industry categories corresponding to the level 3 classification of industries provided by DataStream. The industry categories consist of resources, basic industries, general industries, cyclical consumer goods, non-cyclical consumer goods, cyclical services, non-cyclical services, utilities, information technology, and financials.

For our sample emerging markets, we use the S&P/IFCG index returns during the period 1989 - 2004. The S&P/IFCG index was introduced by International Finance Corporation (IFC) in 1981 and has been maintained by Standard & Poor's since 2000. The S&P/IFCG index targets an aggregate market capitalization of 70-80% of the total capitalization of all exchange-listed shares. The weekly S&P/IFCG index is available from December 1988.[2] We select 14 emerging markets for which the weekly S&P/IFCG indices are available from the inception. They are: Argentina, Brazil, Chile, Columbia, India, Jordan, Korea, Malaysia, Mexico, the Philippines, Taiwan, Thailand, Turkey, and Venezuela. All stock index returns are adjusted for dividends.

Figure 1.1 provides scatter plots of the risk-return characteristics of our 17 sample developed markets 'relative to' the cross-market average in three separate years, i.e.,

[2] In choosing our sample period, we are also constrained by the fact that as we go back further, the number of emerging markets covered by the database declines sharply. For more information on the S&P/IFCG index, refer to its website (www.indices.standardpoors.com).

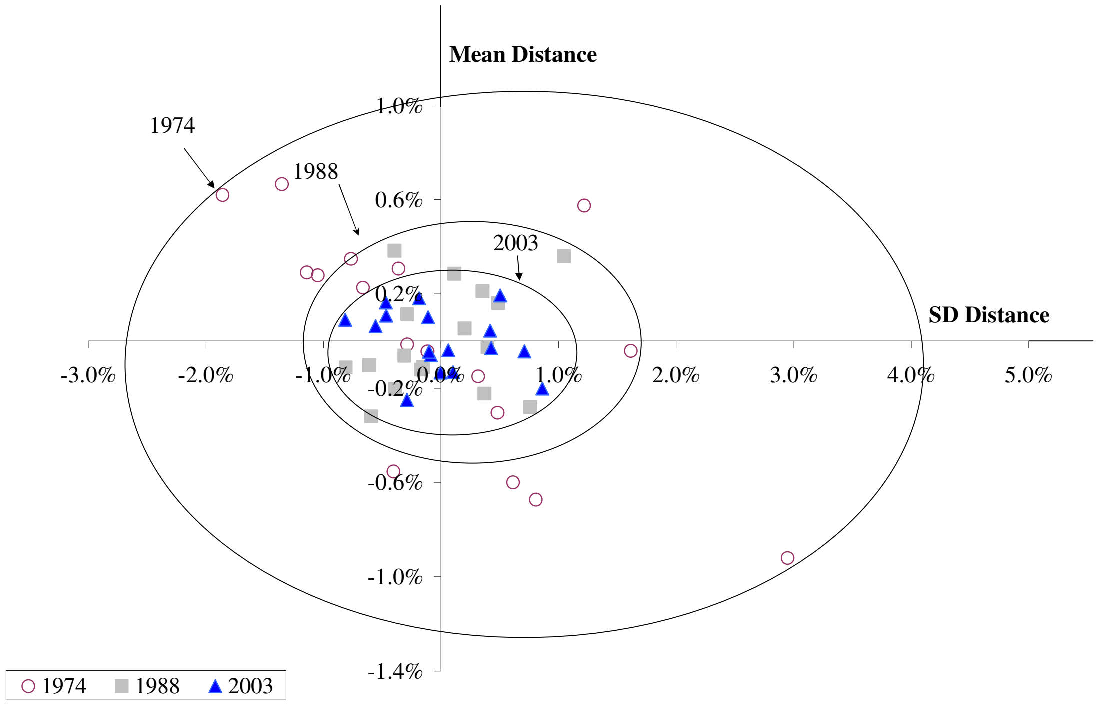

Figure 1.1. The Risk-Return Distance among 17 Developed Markets for 1974, 1988, and 2003

1974, 1988, and 2003. For each year, the origin in the figure denotes (i) the cross-market average of mean returns and (ii) the cross-market average of standard deviations for 17 markets[3]. We use weekly dollar returns to compute these parameters. The y-axis thus measures how much the mean return for a market deviates from the cross-market average of mean returns during a particular year. Similarly, the x-axis measures how much the standard deviation for a market deviates from the cross-market average of standard deviations. For the U.S., for example, the mean and standard deviation of weekly returns were 0.46% and 2.18%, respectively, in 2003. For the same year, the cross-market average among the 17 sample markets was 0.71% for the mean and 2.46% for the standard deviation. The coordinates for the U.S, therefore, are –0.25% (= 0.46% - 0.71%)) on the y-axis and –0.28% (= 2.18% - 2.46%) on the x-axis for the year. As can be seen from Figure 1.1, the ellipse encompassing all the observations for each year becomes successively smaller over time. Our first look at the data, albeit cursory, thus suggests that the risk-return characteristics of international stock markets might have converged toward each other over time. In what follows, we formally investigate this possibility.

Methodology

To formally test the risk-return convergence, we first introduce a risk-return distance measure, which is similar in concept to the (dis)similarity measure in cluster

[3] There are two types of average in this study: one is the time series average for individual country during a certain period and the other is the cross-market average for sample markets. To avoid confusion, we need to clearly differentiate these two types. We thus adopt the convention of using (i) the term "mean" for each individual country and (ii) the term "average" for overall sample markets.

analysis. Cluster analysis is a term for a group of quantitative methods for examining multivariate data with a view to grouping the data based on the properties they have[4]. The main objective of cluster analysis is to define the structure of the data by placing the most similar observations into groups. It is thus necessary to measure (dis)similarities between observations as the first step to group the data.

One of the most commonly used methods for measuring (dis)similarities in cluster analysis is the Euclidean distance. Suppose that the number of characteristics for an observation is p and that each characteristic can be represented by a variable. Then, two observations can be represented by points in p-dimensions with coordinates (x_1, x_2, …, x_p) and (y_1, y_2, …, y_p) respectively. The Euclidean distance between two observations, d_{xy}, is computed by the following equation:

$$d_{xy} = \sqrt{\sum_{i=1}^{p} (x_i - y_i)^2} \tag{1}$$

The greater the Euclidean distance between the observations, the more dissimilar they are in terms of their characteristics. In our study, each market corresponds to an observation that is represented by two-dimensional characteristics, i.e., risk and return.

Applying the (dis)similarity measure in cluster analysis, we compute the risk-return distance for a particular market as the Euclidean distance between (i) a pair of mean return and standard deviation for a market and (ii) a pair of the cross-market average of mean returns and the cross-market average of standard deviations for N markets. For each market, we compute the risk-return distance for each observation

[4] For detailed description of cluster analysis, refer to Hair, Anderson, Tatham, and Black (1998) or Everitt, Landau, and Leese (2001).

period. To compute this distance measure, however, we first need to compute the return distance and risk distance measures separately.

We measure the 'return distance' of a market from the cross-market average for N markets based on the absolute difference between the mean return for the market and the cross-market average return. Specifically, the return distance for market i during the period t (DR_{it}) is computed as follows:

$$DR_{it} = \left| \overline{R}_{it} - \frac{1}{N}\sum_{i=1}^{N} \overline{R}_{it} \right|, \; i = 1, \ldots, N; \; t = 1, \ldots, T, \qquad (2)$$

where $\overline{R}_{it}$ is the mean return for market i during the period t. Similarly, we measure the 'risk distance' of a market based on the absolute difference between the standard deviation for the market and the cross-market average of standard deviations for N markets. The risk distance for market i during the period t (DS_{it}) is thus computed as follows:

$$DS_{it} = \left| SD_{it} - \frac{1}{N}\sum_{i=1}^{N} SD_{it} \right|, \; i = 1, \ldots, N; \; t = 1, \ldots, T, \qquad (3)$$

where SD_{it} is the standard deviation for market i during the observation period t.

Since variables with larger dispersions would have a greater impact on the (dis)similarity measure than those with smaller dispersions, it is conventional in cluster analysis to normalize the variables before computing the (dis)similarity measure.[5] In

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5 A popular method of normalization is the conversion of each variable to standard scores by subtracting the average and dividing by the standard deviation of each variable. However, this standardization method , that is referred to as autoscaling or standard scoring, cannot be applied directly to our two variables (DR_{it} and DS_{it}) because this standardization method would not preserve the dispersion structure in our data. In this

computing the ‘normalized risk-return distance’, we use the proportion of a variable to the sum of the two variables as its weight. To be compatible with the Euclidean distance measure, we determine the weight for each variable as follows:

$$W(DR) = \sqrt{\sum_{i=1}^{N}\sum_{t=1}^{T} DR_{it}^2 \Big/ (\sum_{i=1}^{N}\sum_{t=1}^{T} DR_{it}^2 + \sum_{i=1}^{N}\sum_{t=1}^{T} DS_{it}^2)} \tag{4}$$

$$W(DS) = \sqrt{\sum_{i=1}^{N}\sum_{t=1}^{T} DS_{it}^2 \Big/ (\sum_{i=1}^{N}\sum_{t=1}^{T} DR_{it}^2 + \sum_{i=1}^{N}\sum_{t=1}^{T} DS_{it}^2)} \tag{5}$$

where W(DR) is the weight for the return distance variable and W(DS) is the weight for the risk distance variable. We thus compute the risk-return distance (DRS_{it}) in such a way that each variable is normalized by its own weight:

$$DRS_{it} = \sqrt{AdjDR_{it}^2 + AdjDS_{it}^2} = \sqrt{(DR_{it} / W(DR))^2 + (DS_{it} / W(DS))^2}\ ,$$

$$i = 1, \ldots, N;\ \ t = 1, \ldots, T. \tag{6}$$

Since we don’t assume any asset pricing model or factors in computing the risk-return distance, our method is essentially model-free and highly robust.

Once we compute the risk-return distance for each market according to Equation (6), we compute the cross-market average (or median) of the risk-return distance measures for N markets for each period. We then examine if there is any time trend in the cross-market average (or median) risk-return distance. If the cross-market average (or median) risk-return distance shows a significant downward (upward) time trend, we will be led to conclude that the risk-return characteristics of international stock markets have

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paper, we are concerned with the time trend in the dispersion structure and thus need to preserve the dispersion structure.

converged (diverged), becoming more similar (dissimilar) to each other over time. We compute the distance measures for each six-month period during 1974 – 2004.

Evolution of the Risk-Return Characteristics among Developed Markets

In this section, we (i) compute the risk-return distance measures based on the formula developed in the previous section, (ii) test the convergence hypothesis, and (iii) discuss the factors related to the differential speed of convergence of individual stock markets toward the international average risk-return characteristic.

Time Trend in the Risk-Return Distance Measure

Table 1.1 reports the cross-market average of the risk-return distance (DRS) measures for 17 developed markets for each six-month period during 1974─2004. Table 1.1 also provides separately the cross-market average return distance (DR) and risk distance (DS) measures. All the distance measures reported here are computed based on the weekly stock market index returns in U.S. dollar terms. During our sample period 1974-2004, the average return distance is 0.35%, whereas the average risk distance is 0.65%. This means that during our sample period, the absolute difference between the return (standard deviation) for a typical market and the cross-market average return (standard deviation) is 0.35% (0.65%) per six-month period. Since the risk distance is substantially greater than the return distance, we normalize these distances so that the two variables may have similar impacts on the risk-return distance measure[6]. The cross-

[6] The weight used for normalization is 0.479 for the return distance (DR) and 0.878 for the risk distance (DS). It turned out, however, that the qualitative results of this paper do not depend on the normalization. The correlation between the cross-market average risk-

Table 1.1. Cross-Market Average of the Risk-Return Distance Measures for 17 Developed Stock Markets, 1974 – 2004

Year	Semi-annual period	Risk-return distance (%)	Return distance (%)	Risk distance (%)	Year	Semi-annual period	Risk-return distance (%)	Return distance (%)	Risk distance (%)
1974	1	1.17	0.25	0.85	1990	1	1.12	0.32	0.72
	2	1.97	0.65	1.13		2	1.23	0.26	0.85
1975	1	2.31	0.63	1.56	1991	1	0.84	0.29	0.45
	2	0.86	0.25	0.55		2	0.69	0.23	0.36
1976	1	1.34	0.41	0.82	1992	1	0.86	0.31	0.41
	2	1.38	0.29	0.99		2	1.21	0.31	0.84
1977	1	0.98	0.30	0.58	1993	1	0.99	0.25	0.65
	2	1.18	0.45	0.53		2	1.02	0.36	0.50
1978	1	0.93	0.34	0.42	1994	1	1.04	0.31	0.61
	2	1.02	0.21	0.72		2	0.72	0.19	0.46
1979	1	0.93	0.27	0.55	1995	1	1.04	0.27	0.69
	2	1.26	0.44	0.65		2	0.50	0.17	0.25
1980	1	1.32	0.43	0.69	1996	1	0.70	0.15	0.52
	2	1.54	0.52	0.90		2	0.91	0.34	0.38
1981	1	1.91	0.66	0.97	1997	1	0.71	0.22	0.36
	2	1.29	0.35	0.81		2	1.46	0.52	0.75
1982	1	1.15	0.38	0.64	1998	1	1.78	0.60	0.98
	2	1.70	0.61	0.79		2	1.26	0.39	0.77
1983	1	1.07	0.26	0.66	1999	1	1.44	0.61	0.45
	2	1.24	0.33	0.78		2	0.86	0.30	0.44
1984	1	1.17	0.39	0.59	2000	1	1.04	0.32	0.55
	2	1.22	0.41	0.67		2	0.77	0.26	0.35
1985	1	1.54	0.53	0.77	2001	1	0.83	0.27	0.38
	2	1.63	0.61	0.71		2	0.86	0.25	0.46
1986	1	1.48	0.47	0.82	2002	1	0.81	0.26	0.46
	2	1.07	0.32	0.64		2	1.26	0.20	0.98
1987	1	1.21	0.48	0.43	2003	1	0.92	0.22	0.65
	2	1.91	0.28	1.53		2	0.57	0.13	0.38
1988	1	1.19	0.41	0.66	2004	1	0.53	0.14	0.30
	2	0.70	0.27	0.28		2	0.65	0.26	0.25
1989	1	1.19	0.38	0.63	Average		1.14	0.35	0.65
	2	0.97	0.28	0.57					

return distance measures with and without normalization is 0.968 during our sample period.

market average of the risk-return distance (DRS) thus computed turns out to be 1.14% during our sample period.

As can be seen from Figure 1.2, which plots the cross-market average risk-return distance measure over time, there is a clear downward trend in the risk-return distance during our sample period. Figure 1.2 also shows that the risk-return distance measure fluctuates substantially about the time trend, probably reflecting the varying market conditions. Although unreported in the paper, we also notice quite similar downward time trends in both the return and risk distance measures. Our observations here thus suggest that the risk-return characteristics of international stock markets have become increasingly similar over time, and that this risk-return convergence reflects the dual convergences in the return as well as risk dimensions.

Tests of the Convergence Hypothesis

To formally test if there is indeed a significant time trend in the cross-market average (or median) risk-return distance measure, we estimate the following regression and check if the beta coefficient is significantly different from zero:

$$DRS_t = \alpha + \beta * \text{Time} + \varepsilon_t, \ \text{Time} = 1, \dots, 62 \qquad (7)$$

We estimate the above time trend model using the distance measures computed from U.S. dollar returns as well as local currency returns in order to check if currency exchange rate changes might have affected the time trends in the distance measures.

When we test if a variable has a time trend, an appropriate test procedure depends on the property of error term. If the error term has a mild serial correlation, the standard test would be reliable. However, if the error term has a strong serial correlation or a unit

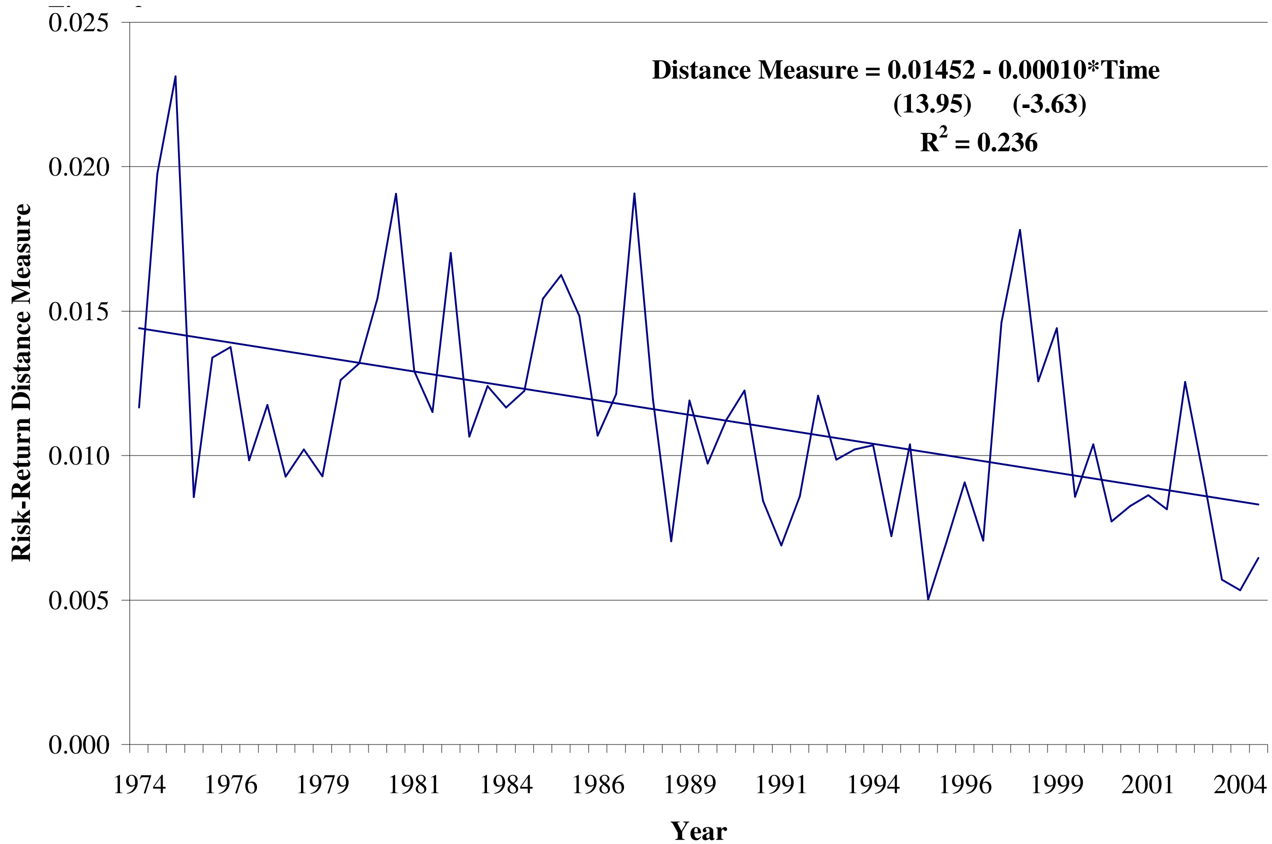

Figure 1.2. Time Trend in the Cross-Market Average Risk-Return Distance Measure for 17 Developed Markets

root, the standard test performs poorly and the statistic from the test would not be reliable. For this reason, we first test if our sample has errors with a unit root. To this end, we employ the augmented Dickey-Fuller (ADF) test[7]. The null hypothesis of the ADF test is that errors from the regression model of Eq. (7) have a unit root with no constant or time trend[8]. If the null hypothesis is rejected, the statistic from the standard test is likely to be valid. For the standard test, we rely on the Newey-West heteroskedastic autocorrelation consistent t-statistics.

Table 2.2 reports test results for the convergence hypothesis for our sample developed markets. The table also reports separate test results for the return and risk convergences[9]. The test results with U.S. dollar returns and local currency index returns are reported

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[7] We also used a non-parametric unit-root test proposed by Breitung (2002) and obtained qualitatively similar results to those from the ADF test. The non-parametric test results are available upon request.

[8] The number of lags for the ADF test is determined by the method recommended in Campbell and Perron (1991). The maximum lag we consider is 6. The order of lag is reduced by one until the coefficient on the last included lag is found to be significant at the 10 percent level.

[9] As an alternative approach to examining the convergence in risk and return, we also use the so-called σ-convergence. This convergence measure has been extensively used in the economic growth literature (for the literature review on growth economics and concepts of convergence in the literature, refer to Durlauf and Quah (1999)). In a study of convergence in economic growth across the United States and European regions, Barro and Sala-i-Martin (1991) introduced the concept of σ-convergence. In their paper, σ-convergence is said to occur when the cross-sectional standard deviation of per capita income among regions diminishes over time. Under this definition, diminishing cross-sectional standard deviation for standard deviations or returns over time can be interpreted as evidence of the convergence for risk or return. The results from this approach are qualitatively similar to those from the Euclidean distance adopted by the current paper and available upon request. The disadvantage of σ-convergence is that it cannot simultaneously consider multivariate attributes of the observation. The Euclidean distance approach does not suffer from this problem.

respectively in Table 2.2. It is first noted from Table 2.2 that for every regression, the ADF test rejects the null hypothesis that errors have a unit root at the 1 percent significance level, implying that the standard test is likely to be reliable. It is noted that for every distance measure, the coefficient of time variable (β) is negative and significant at the 5 percent level or better based on the Newey-West adjusted t-statistics, t_{HAC}. Thus, the test results presented in Table 2 lead us to conclude that the risk-return characteristics of 17 sample markets have converged significantly toward each other during our sample period and that this international risk-return convergence is driven by the dual convergences in return and risk distances. Furthermore, the above conclusion holds, regardless of whether the risk and return distances are measured in U.S. dollar or local currency terms. In fact, the test results for local currency returns are almost identical to those for U.S. dollar terms, implying that exchange rate changes have no noticeable effects on the evolutionary pattern of the risk-return characteristics of international stock markets during our sample period. In what follows, we examine the convergence issues with U.S. dollar returns.

The documented risk-return convergence is also economically significant. The intercept of the regression can be interpreted as the projected 'initial' risk-return distance from the cross-market average risk-return characteristic, whereas the slope may be interpreted as the speed of convergence toward the cross-market average. As shown in Table 2.2, the projected 'initial' risk-return distance from the cross-market average is 0.01452. On the other hand, the projected risk-return distance from the cross-market average for the last observation period, i.e., the second half of 2004, is 0.00832. This implies that the average risk-return distance has decreased by about 43 percent over

Table 1.2. Tests of the Convergence Hypothesis for 17 Developed Markets, 1974 - 2004

U.S. Dollar Index Returns	Dependent Variable	Intercept(α)*100	Time(β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ statistic)
Cross-Market Average	risk-return distance	1.452	-0.010	-3.63***	0.236	-3.92***
	return distance	0.442	-0.003	-2.60**	0.156	-3.91***
	risk distance	0.855	-0.007	-3.79***	0.208	-7.00***
Cross-Market Median	risk-return distance	1.246	-0.008	-3.64***	0.210	-5.95***
	return distance	0.356	-0.002	-2.03**	0.101	-4.35***
	risk distance	0.698	-0.005	-3.66***	0.194	-6.36***
Local Currency Index Returns	Dependent Variable	Intercept(α)*100	Time(β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ statistic)
Cross-Market Average	risk-return distance	1.432	-0.010	-3.09***	0.218	-5.61***
	return distance	0.400	-0.003	-2.56**	0.166	-5.90***
	risk distance	0.864	-0.007	-2.71***	0.175	-6.20***
Cross-Market Median	risk-return distance	1.215	-0.008	-2.67***	0.185	-5.38***
	return distance	0.312	-0.002	-2.08**	0.114	-5.70***
	risk distance	0.722	-0.005	-2.51**	0.148	-6.17***

our sample period 1974─2004. International stock markets thus have become substantially less distinctive from each other in terms of risk-return characteristics.

Having established a significant risk-return convergence at the market average level, we now examine the issue at the individual market level. To test the convergence hypothesis for an individual market, we estimate the time trend model of Eq. (7) with the risk-return distance measure for the individual market, rather than the cross-market average distance, as the dependent variable. It is recalled that the risk-return distance for an individual market is computed according to Eq. (6).

Table 1.3 presents the test results of risk-return convergence for each of the 17 individual markets. Since the ADF test rejects the null hypothesis that errors have a unit root at least at the 5 percent significance level for each market, we rely on Newey-West adjusted t-statistics for interpreting our estimation results. For the risk-return distance measure (DRS), we reject the null hypothesis that there is no convergence at the 10 percent level or better for 11 out of 17 markets. The 11 markets exhibiting a significant risk-return convergence are: Australia, Austria, Canada, Denmark, France, Germany, Hong Kong, Ireland, Italy, Switzerland, and the United Kingdom. Four markets, i.e., the Netherlands, Singapore, South Africa, and the United States, exhibit a convergent tendency, albeit insignificant. Notably, the time trend coefficient (β) is essentially zero for Belgium. This implies that Belgium is at the focal point of international convergence. One market, Japan, is found to exhibit a statistically significant tendency to 'diverge' from the rest of the sample markets in terms of risk-return characteristics. This unusual result for Japan is driven by the return divergence; the Japanese risk distance exhibits a convergence, albeit statistically insignificant. The Japanese return divergence, in turn, is attributable to the prolonged depression of Japanese stock market throughout the 1990s when other markets experienced bullish conditions.

For the return distance (DR), we reject the null hypothesis of no convergence for 8 out of 17 markets at the 10 percent level or better[10]. For the risk distance (DS), on the other hand, we reject the null hypothesis for 7 out of 17 markets at the 10 percent level or better[11]. As can be seen from the F-test results provided in the last row of Table 1.3, we reject the hypothesis that all the time trend coefficients for 17 markets are jointly zero for each distance measure. In testing the hypothesis, we choose to employ the F statistic proposed by Vogelsang and Franses (2005)[12]. Overall, our test results in Table 1.3 show that the risk-return convergence among our sample markets is not driven by a few outlier markets. It is noted, however, that not all individual markets are expected to converge toward the international average since some markets can be near the focal point of convergence, to begin with.

We also perform pair-wise tests for the equality of time trend parameters (or speed of convergence) among 17 individual markets. Table A.1 provides the test results. As can be seen from the appendix, for the U.S., we reject the null hypothesis of equal time trend β with the following eight markets: Australia, Austria, Canada, Denmark,

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[10] The eight markets are Canada, Denmark, France, Germany, Hong Kong, Ireland, Italy, and the United Kingdom.

[11] The seven markets are Australia, Austria, Denmark, Germany, Hong Kong, Ireland, and Switzerland.

[12] Vogelsang and Franses test has better finite sample size than the traditional Wald test, given that the series with deterministic trends have stationary errors. Vogelsang and Frances (2005), in fact, propose two F statistics. We use their second F statistic. They document that the size of the first and second F statistics are similar but the second statistic has a higher power, suggesting that the second F statistic is preferable.

Table 1.3. Tests of the Convergence Hypothesis for Individual Developed Markets, 1974 – 2004

Market	Risk-return distance					Return distance					Risk distance				
	Intercept (α)*100	Time (β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ stat)	Intercept (α)*100	Time (β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ stat)	Intercept (α)*100	Time (β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ stat)
Australia	1.429	-0.011	-2.69***	0.060	-7.19***	0.375	-0.002	-1.29	0.025	-7.83***	0.820	-0.007	-2.08**	0.043	-6.53***
Austria	2.142	-0.019	-2.85***	0.089	-6.11***	0.540	-0.003	-1.23	0.012	-2.92***	1.470	-0.017	-3.98***	0.172	-4.61***
Belgium	0.903	-0.000	-0.12	0.000	-5.44***	0.290	-0.001	-0.34	0.003	-4.78***	0.488	0.000	0.09	0.000	-7.95***
Canada	1.373	-0.009	-2.52**	0.093	-6.72***	0.440	-0.004	-2.51**	0.097	-3.52***	0.789	-0.005	-1.66	0.047	-5.68***
Denmark	1.157	-0.011	-2.78***	0.136	-5.99***	0.410	-0.004	-1.97*	0.076	-2.87***	0.634	-0.006	-2.53**	0.097	-5.76***
France	1.067	-0.009	-2.23**	0.076	-6.95***	0.456	-0.006	-3.25***	0.133	-7.01***	0.534	-0.004	-1.32	0.028	-4.41***
Germany	1.160	-0.008	-2.20**	0.073	-7.49***	0.340	-0.002	-1.75*	0.033	-4.40***	0.713	-0.005	-1.84*	0.070	-6.62***
Hong Kong	3.006	-0.030	-2.49**	0.123	-4.26***	0.872	-0.009	-2.99***	0.099	-4.76***	1.770	-0.017	-1.93*	0.080	-3.98***
Ireland	1.446	-0.016	-2.96***	0.168	-6.87***	0.550	-0.006	-2.35**	0.124	-2.56**	0.794	-0.010	-3.03***	0.137	-7.22***
Italy	1.835	-0.014	-1.71*	0.076	-4.24***	0.555	-0.005	-2.23**	0.081	-4.87***	1.002	-0.008	-1.26	0.037	-5.64***
Japan	1.107	0.005	1.88*	0.019	-7.67***	0.311	0.005	1.90*	0.052	-8.89***	0.722	-0.002	-0.63	0.004	-6.79***
Netherlands	1.142	-0.004	-1.53	0.027	-5.00***	0.203	-0.001	-1.10	0.014	-4.50***	0.677	-0.002	-0.54	0.005	-5.60***
Singapore	1.545	-0.010	-1.31	0.028	-6.18***	0.556	-0.004	-0.90	0.021	-6.30***	0.806	-0.006	-1.30	0.020	-7.15***
South Africa	1.804	-0.008	-1.31	0.022	-2.52***	0.557	-0.002	-0.67	0.006	-7.45***	1.105	-0.007	-1.43	0.032	-3.45***
Switzerland	1.085	-0.006	-2.55**	0.076	-7.71***	0.298	-0.001	-0.69	0.007	-8.14***	0.730	-0.007	-3.17***	0.147	-7.20***
U.K.	1.403	-0.015	-2.13**	0.148	-3.26***	0.492	-0.007	-3.46***	0.207	-8.33***	0.687	-0.005	-0.93	0.034	-3.07***
U.S.	1.179	-0.004	-1.16	0.023	-4.54***	0.250	0.000	0.25	0.001	-9.19***	0.797	-0.006	-1.61	0.053	-6.61***
F-test (H_0: All β's = 0)	597.08***					920.14***					465.73***				

Hong Kong, Ireland, Italy, and Japan. The null hypothesis cannot be rejected for the other eight markets. For Hong Kong, the null hypothesis of equal β is rejected with all other countries except Austria. For Japan, the null is rejected with all other markets except Belgium.

Factors Related to the Speed of Convergence

Our results in Table 1.3 clearly show that the speed of convergence varies greatly across individual markets. This situation means that the risk-return characteristics of individual markets have been evolving toward the international average, but at quite different paces. Given that the speed of convergence or the time trend coefficient (β) varies greatly across individual markets, it seems logical to ask the following question: What factors are related to the speed of convergence?

It is first noted from Table 1.3 that the slope coefficient (β) appears to be correlated with the intercept (α) across markets. For instance, Belgium, the market with zero speed of convergence, has the lowest intercept (α) among all of our sample markets. By contrast, Hong Kong, the market with the most negative β, is found to be the one with the highest α. Canada has a medium β, coupled with a medium α. In order to verify this intriguing association, we plot the β coefficient against α coefficient for 17 individual markets in Figure 1.3. The figure indeed confirms that there is a rather strong negative relationship between the intercept and slope of the time trend regressions for our sample markets. As previously mentioned, the intercept of the regression can be interpreted as the projected 'initial distance' of an individual market from the cross-market average risk-return characteristic, whereas the slope may be interpreted as the speed of convergence of the market toward the international average. To be precise, the speed of convergence is the negative of the slope, i.e., (-1)β.

In light of the above interpretation, the strong negative relationship between the intercept and slope of the time trend regression illustrated in Figure 1.3 implies the following: The farther away a market was initially from the rest of markets in terms of risk-return characteristics, the faster the market converges toward the cross-market average. Accordingly, individual markets such as Hong Kong and Austria have both a high intercept and high speed of convergence, whereas such markets as Belgium, the Netherlands, and the U.S. have both a low intercept and low speed of convergence.

There are groups of countries for which we observe similar initial distances from and the speeds of convergence toward the cross-market average risk-return characteristic. For example, France and Germany show similar initial distances from and the speeds of convergence toward the cross-market average. We also see a similar pattern for the U.K., and Ireland. Geographical proximity, however, does not always imply similar α-β combinations. For example, the U.S. has a α-β combination that is very close to that of the Netherlands but significantly different from that of Canada. It is interesting to note that Canada exhibits a significant risk-return convergence toward the cross-market average, whereas the U.S. does not.[13]

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[13] Jorion and Schwartz (1986) document that the Canadian and U.S. stock markets were segmented during their sample period 1968 – 1982. Mittoo (1992) finds that the two North American stock markets were segmented during the period 1977 – 1981 but became integrated later during the period 1982 - 86. These studies suggest that the Canadian and U.S. stock markets were different from each other in terms of risk-return characteristics at least during an earlier part of our sample period.

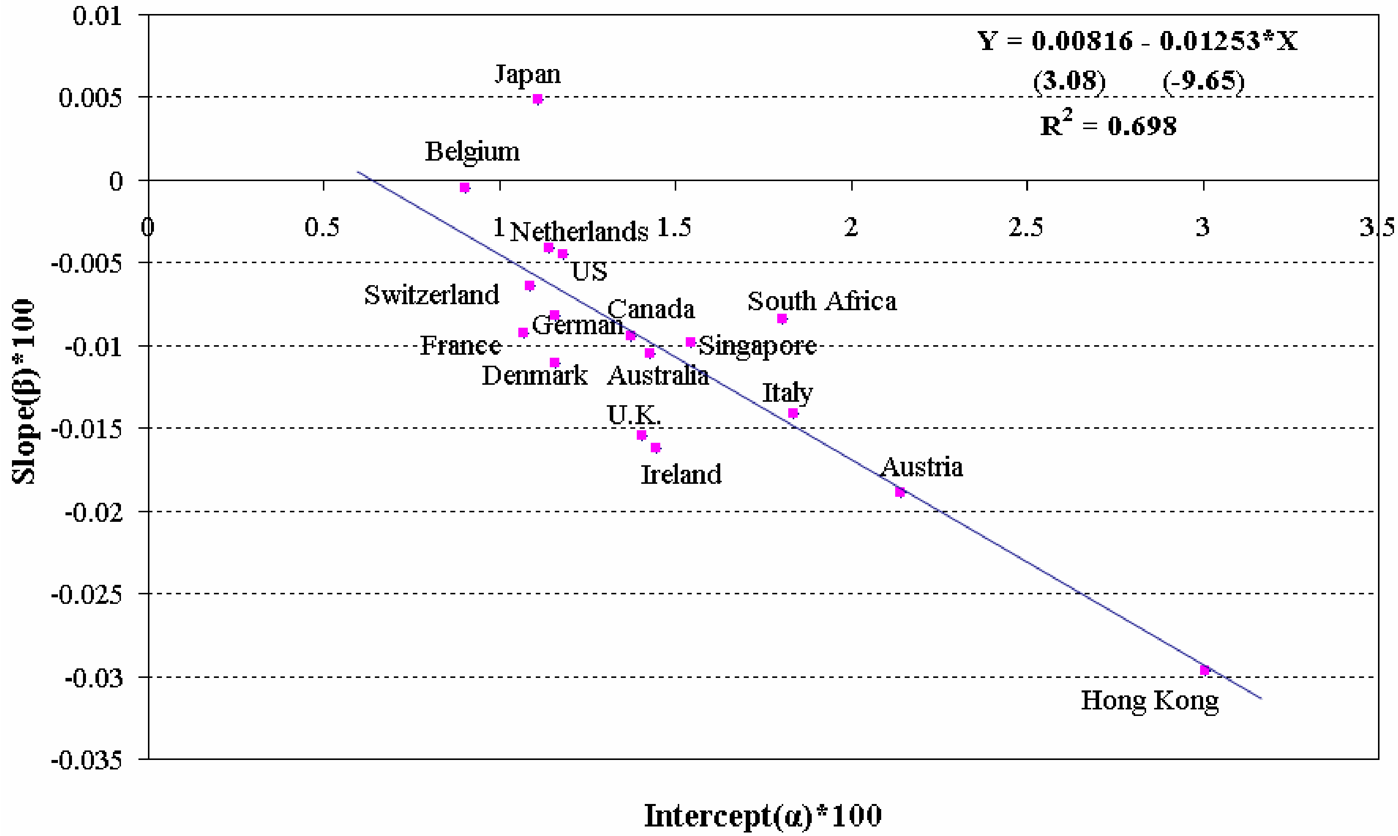

Figure 1.3. Relationship between the Intercept and Slope of Time Trend Regression of the Risk-Return Distance Measures for 17 Developed Markets

Next, we further investigate what other factors may be related to the speed of convergence. We consider the size of equity market, the ratio of equity market capitalization to GDP, dividend yield, and the ratio of exports plus imports to GDP as other possible explanatory variables. We expect that smaller markets may adjust more than larger markets as markets become integrated. We compute the mean equity market capitalization of each market during our sample period and use the logarithm of the mean equity market capitalization as the size of the market. Bekaert and Harvey (1995) explore an asset pricing model where the likelihood of market integration is allowed to vary over time. In their analysis, two information variables, i.e., dividend yield and equity market capitalization as a proportion of GDP, are associated with the likelihood of market integration. They argue that dividend yields decrease and the ratio of market capitalization to GDP increases when markets become integrated. Thus, we expect that the speed of convergence may be higher for a market whose dividend yield (the market capitalization to GDP ratio) declines (rises) faster than other markets over time. On the other hand, Dumas, Harvey, and Ruiz (2003) develop a model which links the correlations of international stock markets to those of countries' outputs and find that their model correlation under the hypothesis of market integration matches observed correlation. Also, Forbes and Chinn (2004) study what explains the linkage in bond and stock markets between countries and find that direct trade between countries is the most important factor in determining the linkage in bond and stock markets. Motivated by these studies, we include growth rate in GDP and the ratio of exports plus imports to GDP as additional explanatory variables. We expect that the speed of convergence would be higher, the higher the speed of convergence in growth rate is or the faster a country's trade to GDP ratio increases relative to other countries.

Since we study the long-run trend of convergence, we also use the long-term trend in dividend yield, the ratio of stock market capitalization to GDP, grow rate in GDP, and the ratio of trade to GDP for each market. To measure the long-term trends in these variables, we take a similar approach as we did for the risk-return distance. For dividend yield, we compute the mean monthly dividend yield for a market and calculate the absolute difference between the mean dividend yield for the market and the cross-market average dividend yield for 17 markets every year. Then we regress the absolute difference on the time variable and take the time coefficient as the long-run trend in dividend yield for the market. For GDP growth rate, we compute the annual growth rate in GDP for a country and take the absolute difference between the growth rate for the country and the cross-country average growth rate for 17 countries every year. Then we regress the absolute difference on the time variable and take the time coefficient as the long-run trend in GDP growth rate for the country. For the ratio of stock market capitalization to GDP (the ratio of trade to GDP), we compute the ratio of the mean stock market capitalization to GDP (the ratio of trade to GDP) for a market and calculate the difference between the ratio for the market and the cross-market average ratio for 17 markets every year. Then we regress the difference on the time variable and use the time coefficient as the long-run trend in the ratio of stock market capitalization to GDP (the ratio of trade to GDP) for the market[14].

Table 1.4 reports the regression results for the speed of convergence. The dependent variable in each regression is the estimated slope (β) from the risk-return convergence tests for individual markets in Table 1.3. The heteroskedasticity-robust t-values are reported in parentheses. In model 1, we regress the slope (β) on the intercept (α) from the risk-return convergence tests in Table 1.3. As we previously discussed, there indeed exists a strong negative relationship between the intercept and slope. The coefficient of the intercept (α) is significantly negative (t-statistic of -9.65) at the 1 percent level, with a R-square value of 0.698[15]. In model 2, we regress the slope (β) on the market size. The coefficient of the market size is significantly positive at the 10 percent level, as expected, suggesting that smaller markets indeed adjust more and have steeper slopes than larger markets. In models 3 and 4 where we regress the slope (β) on the time trends of the ratio of stock market capitalization to GDP and dividend yield respectively, neither of the trend coefficients is found to be significant. GDP growth rate is not significant either,

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[14] We take the absolute difference for dividend yield while we just take the difference for stock market capitalization to GDP and trade to GDP. As a market becomes more integrated with other markets, we expect that the dividend yield for the market may become closer to those for other markets. On the other hand, the stock market capitalization to GDP and trade to GDP ratios for the market may become simply higher, not necessarily converging to other markets, as the market becomes more integrated.

15 When we estimate the intercept and slope for a market, it is well known that there is a negative correlation between these two estimates. Thus, we cannot rule out the possibility that the negative relationship between these two estimates might be an artifact from this statistical property. To take this possibility into account, we regress the slope on the mean of ‘actual’ distance measures over the first two years, instead of the estimated intercept. In this case, the coefficient of the actual distance measure is still significantly negative (t-statistic of -5.09) at the 1 percent level, with a R-square value of 0.539.

Table 1.4. Regression Analysis of the Speed of Convergence: The Case of Individual Developed Markets

	Dependent Variable = Slope (β) from the Convergence Test							
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Constant	0.00008 (3.08)***	-0.00034 (-2.98)***	-0.00010 (-5.56)***	-0.00009 (-3.99)***	-0.00009 (-3.90)***	-0.00010 (-6.68)***	-0.00024 (-1.46)*	-0.00015 (-0.93)
Intercept (α) from the Convergence Test	-0.01253 (-9.65)***							-0.01184 (-3.79)***
Log (Market Cap)		0.00002 (2.06)*					0.00001 (0.99)	0.00002 (1.31)
Trend (Market Cap/GDP)			-0.00104 (-0.94)				0.00006 (0.06)	-0.00064 (-1.01)
Trend (Dividend Yield)				0.03381 (0.76)			0.00960 (0.18)	-0.05779 (-1.21)
Trend (GDP Growth)					0.00047 (0.75)		0.00040 (1.37)	-0.00032 (-0.89)
Trend (Trade/GDP)						-0.00358 (-3.91)***	-0.00306 (-2.24)**	-0.00014 (-0.11)
N	17	17	17	17	17	17	17	17
R^2	0.698	0.153	0.113	0.016	0.087	0.407	0.519	0.783

when the slope is regressed on the time trend of GDP growth rate in model 5. However, when the slope is regressed on the time trend of the ratio of trade to GDP in model 6, we find a significant, negative coefficient. This implies that the more open a country becomes in terms of international trade, the faster converges the country's stock market toward other markets. In model 7, we include all four additional factors, i.e., market size and trends in the ratio of market capitalization to GDP, dividend yield, GDP growth rates, and the ratio of trade to GDP, as independent variables. The ratio of trade to GDP is still significant at the 5 percent level, but the other four variables, including the market size variable, are insignificant. In model 8, we include the intercept (α) from the time trend regression as well as the five additional variables as independent variables. Estimation of the model shows that the intercept (α) is the only significant variable and dominates all the other variables. The ratio of trade to GDP becomes insignificant when considered with the intercept (α). This suggests that the trade to GDP ratio may have a high correlation with the intercept (in fact, 0.60) and proxy the latter to some extent. Overall, our regression analysis indicates that the initial risk-return distance from the international average mainly drives the speed of convergence of individual markets toward the international average.

What Drives the Risk-Return Convergence?

Heston and Rouwenhorst (1994), Griffin and Karolyi (1998), and others find that the variation in national stock market returns can scarcely be explained by the industrial compositions of the economies. These studies maintain that low international correlations are mainly due to country factor, rather than industry factor. Recently, however, Baca, Garbe, and Weiss (2000) and Cavaglia, Brightman, and Aked (2000) report that the importance of industry factor has increased over time and that the impact of industry factor is nearly equal to or even larger than that of country factor. In a related study, Carrieri, Errunza and Sarkissian (2004) document that the industrial structure has become increasingly aligned across markets, especially across developed markets.

The aforementioned studies point to two possible drivers for the risk-return convergence among international stock markets: a decline in country effect or a rise in industry effect. If country effect has decreased over time as global capital markets have been integrating, we may observe a risk-return convergence. On the other hand, if the industrial structure across markets has become more similar and industry effect has increased, we may also observe a risk-return convergence. In this section, we investigate which of the two effects, country or industry, is the key driver for the risk-return convergence documented in the previous section. In tackling this question, we first generate two separate return series, one representing industry effect and the other country effect, for each market and conduct the convergence tests separately using each of the two return series.

Table 1.5 provides the industry composition of the DataStream stock market indices during the period 1974 – 2004. The average capitalization value of each market by industry is reported as percentage of the total market capitalization of 17 markets. As discussed in the data description, we use 10 broad industry categories corresponding to the level 3 industry classification provided by DataStream. The U.S. and Japan are the two dominant markets with the combined capitalization share of 71.78 percent (the US: 46.99 percent, Japan: 24.79 percent), followed by the U.K. (8.56 percent), Germany (4.16 percent), and France (2.61 percent). The industrial structure varies substantially across sample markets. Some markets have a well diversified industrial structure (e.g., France, Japan, and the U.S.), while others exhibit a more concentrated industrial structure (e.g., Hong Kong, South Africa, and Switzerland).

Following Heston and Rouwenhorst (1994), we decompose stock market returns into returns related to country and industry effects, respectively. Specifically, we run the following regression to decompose returns for industry j in country c (R_{cj}) into their industry and country components:

$$R_{cj} = \alpha + \beta_1 * I_1 + \beta_2 * I_2 + \ldots + \beta_{10} * I_{10} + \gamma_1 * C_1 + \gamma_2 * C_2 + \ldots + \gamma_{17} * C_{17} + e_{cj},$$

$$c = 1, 2, \ldots, 17; \ j = 1, 2, \ldots, 10, \qquad (8)$$

where I_j (C_c) is a dummy variable which takes the value of one if the return is from the industry j (country c) and zero otherwise. Since each return belongs to one country and one industry, the regression has a multicollinearity problem if dummy variables are defined for every country and industry. Again, following the lead of Heston and Rouwenhorst, we impose the constraint that the value-weighted sums of the industry and country coefficients equal to zero, respectively, to avoid this problem. Thus, we estimate the regression subject to the constraints that

$$\sum_{j=1}^{10} \omega_j \beta_j = 0, \text{ and}$$

$$\sum_{c=1}^{17} \lambda_c \gamma_c = 0,$$

where ω_j and λ_c are the weights of industry j and country c in the world market portfolio

Table 1.5. Industry Compositions of 17 Developed Stock Markets

Market	Total	Industry									
		Resources	Basic Industries	General Industries	Cyclical Consumer Goods	Non-Cylical Consumer Goods	Cyclical Services	Non-Cycle Services	Utilities	Information Technology	Financials
Australia	1.41	0.50	0.16	0.04	0.01	0.11	0.19	0.05	0.01	0.00	0.34
Austria	0.11	0.01	0.02	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.04
Belgium	0.47	-	0.07	0.03	0.00	0.03	0.02	0.02	0.11	0.00	0.19
Canada	2.51	0.56	0.38	0.16	0.01	0.17	0.23	0.07	0.13	0.31	0.50
Denmark	0.29	-	0.01	0.02	0.01	0.07	0.09	0.02	0.00	0.00	0.06
France	2.61	0.34	0.26	0.37	0.25	0.40	0.25	0.23	0.01	0.15	0.36
Germany	4.16	0.00	0.68	0.97	0.47	0.20	0.16	0.25	0.20	0.08	1.15
Hong Kong	1.39	0.01	0.01	0.24	0.01	0.01	0.15	0.13	0.13	0.01	0.70
Ireland	0.15	0.00	0.04	0.00	0.01	0.03	0.01	0.00	-	0.00	0.07
Italy	1.46	0.08	0.07	0.07	0.17	0.01	0.07	0.22	0.06	0.01	0.69
Japan	24.79	0.39	3.38	3.04	2.54	1.79	3.27	1.23	1.45	1.54	6.16
Netherlands	2.08	0.68	0.10	0.18	0.02	0.29	0.18	0.08	-	0.03	0.54
Singapore	0.50	0.00	0.01	0.06	0.00	0.04	0.10	0.06	0.00	0.01	0.22
South Africa	0.88	0.57	0.02	0.10	0.00	0.06	0.03	0.01	-	-	0.10
Switzerland	1.65	-	0.08	0.14	0.02	0.86	0.06	0.02	0.04	0.00	0.42
U.K.	8.56	1.27	0.78	0.59	0.07	1.50	1.45	0.75	0.25	0.06	1.84
U.S.	46.99	5.05	3.08	4.26	2.22	8.39	5.74	3.84	3.16	5.96	5.27
Total	100.00	9.46	9.15	10.27	5.81	13.94	12.01	6.99	5.56	8.16	18.65

respectively.[16] Since the value-weighted sums of the industry and country coefficients equal to zero respectively, the intercept in the regression can be interpreted as the return on the value-weighted world market portfolio. The coefficient β_j can be interpreted as the estimated effect of industry j relative to the return on the world market portfolio. Similarly, the coefficient γ_c can be interpreted as the estimated effect of country c relative to the return on the world market portfolio.

To address the issue of whether the risk-return convergence is driven by country or industry effect, we construct two hypothetical return series for each country – one with country effect and the other with industry effect – using the estimated coefficients of the regression. The hypothetical return for country c with country effect ($r_{c,ce}$) is computed as follows:

$$r_{c,ce} = \hat{\alpha} + \hat{\gamma}_c \text{, c = 1, 2, …, 17.} \tag{9}$$

On the other hand, the hypothetical return for country c with industry effect ($r_{c,ie}$) is defined as follows:

$$r_{c,ie} = \hat{\alpha} + \sum_{j=1}^{10} \chi_{cj} * \hat{\beta}_j \text{, c = 1, 2, …, 17,} \tag{10}$$

where χ_{cj} is the proportion of total market capitalization of country c in industry j. We separately test the convergence hypothesis using the two decomposed return series for 17 sample markets.

[16] The world market portfolio here represents the total market capitalization of 17 countries in our sample. According to DataStream, the total market capitalization of 17 countries accounts for 87.1 percent of the actual world market capitalization as of the end of 2004.

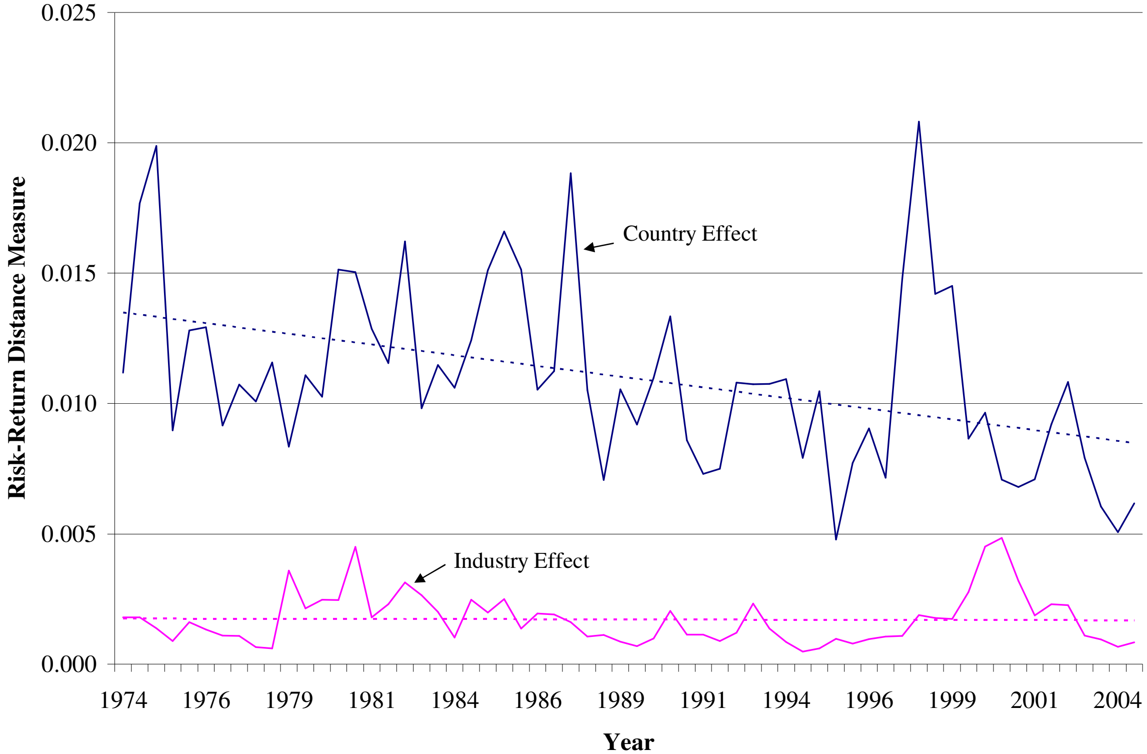

Figure 1.4. Time Trends in the Cross-Market Average of the Risk-Return Distance Measures for 17 Developed Markets: Country vs. Industry Effects

Figure 1.4 separately plots the time trends in the cross-market average of risk-return distance measures with country and industry effects. A few things are noteworthy from the figure. First, the magnitude of the risk-return distance with country effect is much greater than that with industry effect throughout the entire sample period. This implies that the distinct risk-return characteristics of national stock markets much documented in the literature are mainly attributable to country effect, rather than industry effect. What's more important, the risk-return distance measure with country effect clearly trends downward, exhibiting a convergence. By contrast, the risk-return distance measure with industry effect exhibits no clear time trend, either upward or downward. This sharply contrasting behavior implies that the risk-return convergence documented in the previous section is attributable to the declining country effect, rather than the rising industry effect.

Table 1.6 reports the test results for the convergence hypothesis with country and industry effects. Table 1.6 provides the test results with country effect. The test results here are quite similar to those provided in Table 2.2. For each distance measure, the coefficient of the time trend variable is negative and significant at least at the 5 percent level, except for the cross-market median return distance. Table 1.6 also provides the test results with industry effect. It is striking that none of the time trend coefficients are significant. The test results provided in Panel B are qualitatively different from those in Panel A: For every distance measure, there is no convergence with industry effect alone.

Table 1.6. Tests of the Convergence Hypothesis for 17 Developed Markets with Country and Industry Effects, 1974 - 2004

Country Effect	Dependent Variable	Intercept(α)*100	Time(β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ statistic)
Cross-Market Average	risk-return distance	1.358	-0.008	-2.88***	0.176	-5.39***
	return distance	0.429	-0.002	-2.44**	0.140	-4.25***
	risk distance	0.759	-0.005	-2.65**	0.121	-6.44***
Cross-Market Median	risk-return distance	1.099	-0.005	-2.39**	0.118	-5.31***
	return distance	0.341	-0.002	-1.64	0.066	-4.45***
	risk distance	0.622	-0.004	-3.20***	0.129	-6.45***
Industry Effect	Dependent Variable	Intercept(α)*100	Time(β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ statistic)
Cross-Market Average	risk-return distance	0.175	-0.00010	-0.09	0.000	-2.80***
	return distance	0.063	-0.00004	-0.01	0.000	-7.37***
	risk distance	0.086	0.00004	0.05	0.000	-2.80***
Cross-Market Median	risk-return distance	0.138	0.00004	0.31	0.006	-3.03***
	return distance	0.051	0.00008	0.22	0.001	-7.09***
	risk distance	0.059	0.00040	0.54	0.015	-4.09***

associated with international financial integration. As international capital markets become more integrated, the idiosyncratic factors of individual countries become less important over time, resulting in a convergence in risk-return characteristics among national stock markets. Indeed, our unreported results show that the cross-market average variance of residuals from the world market model for 17 sample markets has significantly decreased over our sample period.

Discussions

In this section, we discuss two issues related to the risk-return convergence. First, we check if the risk-return convergence remains robust to the inclusion of the variables representing the overall market conditions, such as the world market volatility and the bullish vs. bearish market conditions. Second, we examine whether the risk-return convergence documented in this study is really another manifestation of the increasing international correlation, a widely recognized phenomenon.

The Risk-Return Convergence Under Different Market Conditions

Previous studies document that there exists an asymmetry in the correlation of international stock markets under different market conditions: The correlation is higher under bearish market conditions than under bullish conditions (e.g. Longin and Solnik (2001)). In this subsection, we study if there is such an asymmetry in the risk-return distance measure. To investigate this issue, we introduce a dummy variable of ‘down’ which takes the value of one if the mean of weekly world market returns for a semi-annual period is negative, and zero otherwise[17]. We also check the effect of the world market volatility on the risk-return distance.

To formally test the convergence hypothesis while controlling for the varying world market conditions, we regress the cross-market average (or median) risk-return distance measure (DRS) on the time variable, standard deviation of the world market returns, 'down' dummy variable, and the interaction term between the standard deviation of the world market returns and the dummy variable:

$$DRS_t = \alpha + \beta_1 * \text{Time} + \beta_2 * SD_t(\text{World}) + \beta_3 * \text{Down}_t + \beta_4 * SD_t(\text{World}) * \text{Down}_t + \varepsilon_t, \quad t = 1,\ldots,62. \tag{11}$$

Table 1.7 reports the test results of the convergence hypothesis under different market conditions. As can be seen from the table, the time trend coefficient is still negative and significant at the 1 percent level for both the average and median risk-return distance measures, confirming that the risk-return characteristics have indeed converged during our sample period. Notably, the coefficient for the standard deviation of the world market return, SD(World), is found to be positive and significant at the 5 percent level or better. This implies that the risk-return distance becomes greater when the world market is more volatile. In contrast, the down dummy variable is found to be insignificant, implying that there would be no asymmetry in the

[17] Among 62 semi-annual periods in our sample, the mean of weekly world market returns is negative for 17 periods and positive for 45 periods.

Table 1.7. Tests of the Convergence Hypothesis for 17 Developed Markets under Different Market Conditions, 1974 – 2004

	Dependent Variable	Intercept	Time	SD(World)	Down	SD(World) *Down	R^2	Unit Root Test for Residuals (τ statistic)
Cross-Market	risk-return distance	0.01048 (6.25)***	-0.00012 (-5.44)***	0.29253 (3.65)***	-0.00289 (-1.20)	0.04673 (0.46)	0.437	-4.07***
Average	return distance	0.00307 (5.03)***	-0.00003 (-3.26)***	0.09845 (3.49)***	0.00115 (1.01)	-0.09375 (-2.04)**	0.251	-4.02***
	risk distance	0.00629 (5.62)***	-0.00008 (-6.49)***	0.16259 (2.50)**	-0.00445 (-2.75)***	0.17476 (1.95)*	0.498	-4.69***
Cross-Market	risk-return distance	0.00973 (5.42)***	-0.00010 (-5.68)***	0.19642 (2.22)**	-0.00309 (-1.25)	0.09426 (0.86)	0.372	-6.71***
Median	return distance	0.00252 (3.55)***	-0.00002 (-2.37)**	0.07635 (2.22)**	0.00145 (1.23)	-0.10216 (-1.95)*	0.171	-4.37***
	risk distance	0.00547 (5.84)***	-0.00007 (-6.74)***	0.10953 (1.87)*	-0.00429 (-3.87)***	0.17982 (3.31)***	0.463	-6.47***

risk-return distance across bullish vs. bearish market conditions. Since the interaction term also turns out to be insignificant, the effect of the world market volatility would not be asymmetric across bullish vs. bearish market conditions. Overall, the time trend together with the world market volatility substantially explains the time series behavior of the risk-return distance in the world market.

Table 1.7 also reports separately the test results of the convergence hypothesis under different market conditions for both the risk and return distances. As is the case with the risk-return distance measure, we still observe the risk and return convergences under different market conditions. The time trend coefficient is negative and significant at least at the 5 percent level for both the risk and return distance measures. Also, both the risk and return distances become greater when the world market is more volatile. It is noted that the coefficient on the standard deviation of the world market return is significantly positive at the 10 percent level or better. Unlike the case of the risk-return distance, the dummy variable is negative and significant at the 1 percent level for the risk distance, implying that the risk distance becomes smaller under the bearish market condition than under the bullish one. For the return distance, however, the dummy variable is insignificant. The interaction term is significantly negative for the return distance but positive for the risk distance, suggesting that the effect of the world market volatility is asymmetric under the bullish vs. bearish market conditions. It is noted that during our sample period, the standard deviation of the weekly world market return is 2.37% when the world market return is negative and 1.51% when the world market return is non-negative.

Does the Increasing Correlation Imply the Mean-Variance Convergence?

As mentioned previously, existing studies, e.g., Login and Solnik (1995), show that the correlation of international stock market returns has increased in recent years. Since international financial integration is often mentioned as an important force behind the increasing correlation, one may conjecture that the risk-return convergence documented in this study might be just another expression of the increasing correlation. In this subsection, we examine the relationship between the increasing correlation and the risk-return convergence using a market model and also provide empirical evidence showing that the increasing correlation does not necessarily imply the risk-return convergence.

Suppose that the return to an individual market i is a linear function of the world market return:

$$R_{it} = \alpha_i + \beta_i R_{Mt} + e_{it} \,. \qquad (12)$$

where Cov (R_{Mt}, e_{it}) = 0, and $E(e_{it}) = 0$. Obviously, this is the market model applied at the international index level.

Once the market model is assumed, the absolute difference in the expected return between market i and the world market is computed as follows:

$$|E(R_{it}) - E(R_{Mt})| = |\alpha_i + (\beta_i - 1)E(R_{Mt})|. \qquad (13)$$

Similarly, the absolute difference in the variance between market i and the world market is calculated as follows:

$$|Var(R_{it}) - Var(R_{Mt})| = |(\beta_i^2 - 1)Var(R_{Mt}) + Var(e_{it})|. \qquad (14)$$

On the other hand, the correlation of returns between market i and the world market is computed as follows:

$$corr(R_{it}, R_{Mt}) = \frac{1}{\sqrt{1 + \frac{Var(e_{it})}{\beta_i^2 Var(R_{Mt})}}} \tag{15}$$

As can be inferred from Eq. (15), the correlation would always increase as the beta increases. However, an increase in the beta would have different effects on the absolute differences in the variance and in the expected return between market i and the world market, depending on the size of the beta. If the beta is greater (less) than unity, an increment in the beta would increase (decrease) the absolute differences in both the parameters. Therefore, the increasing correlation may not always be associated with the risk-return convergence in this simple model.

Japan provides empirical evidence supporting our simple analysis above[18]. As illustrated in Figure B.1, Japan exhibits a risk-return 'divergence' from the rest of international markets and, at the same time, experiences the increasing correlation with other markets during our sample period. The Japanese case, albeit exceptional, clearly shows that the risk-return convergence may not always accompany the increasing correlation. Thus, the increasing correlation and risk-return convergence may be related but distinct phenomena.

Tests of the Convergence Hypothesis for Emerging Markets

In this section, we extend our analysis to a sample of emerging stock markets. Specifically, we examine if the risk-return characteristics of emerging markets have converged

[18] Appendix B simultaneously plots the time trends in the risk-return distance measure and the average international correlation for Japan.

toward those of developed markets. As described in section 2.1, we use the weekly S&P/IFCG index returns for a sample of 14 emerging markets during the period 1989 – 2004.

In order to examine whether the risk-return characteristics of our sample emerging markets converge toward those of developed markets, for each 6-month period, we compute the absolute difference between the mean return (standard deviation) for an emerging market and the cross-market average return (standard deviation) for 17 developed markets. We then calculate the cross-market average (median) risk-return distance measure for 14 emerging markets in the same way as explained in section 2.2[19].

Table 1.8 and Table 1.9 report the results from formally testing if the risk-return characteristics of emerging markets have converged toward those of developed markets. The table also reports separate test results for the return convergence and risk convergence. As can be seen from Table 1.8, the coefficient of the time variable is negative and statistically significant at the 5 percent level or better for each distance measure, with the sole exception of the cross-market median risk distance, This, of course, implies that the risk-return characteristics of our 14

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[19] Figure C.1 shows the time trends in the cross-market average risk-return distance measure and the average correlation for emerging markets. To compute the average correlation, we first compute the pair-wise correlation between each emerging market and each developed market for each six-month period. We then compute, for each period, the average of all the bilateral correlations between emerging and developed markets. As can be seen from the figure, there is a downward trend in the risk-return distance and an upward trend in the average correlation during the period 1989 – 2004. When the average correlation is regressed on the time variable, the intercept is 0.04199 and the time coefficient is 0.00882 (Newey-West t-statistic of 7.09). The time coefficient is significant at the 1 percent level. Thus, the projected initial average correlation is only 4.2 percent, but the projected average correlation increases to 32.4 percent for the second 6-month period of 2004.

sample emerging markets have been converging toward those of developed markets, and that the risk-return convergence reflects both the risk and return convergences.

The risk-return convergence of emerging markets is also economically significant. As can be seen from Table 1.8, the projected ‘initial’ average risk-return distance (i.e., the estimated intercept α) is 0.04657. By comparison, the projected average risk-return distance becomes 0.02705 in the last observation period, i.e., the second 6-month period of 2004. This means that the projected average risk-return distance of our sample emerging markets from the cross-market average of developed markets has decreased by about 42 percent over our sample period 1989 – 2004. It is also noteworthy that the average speed of convergence (the estimated β) for emerging markets, 0.00061, is about six times as fast as that observed for developed markets, 0.00010, during the period 1974 – 2004. The same point can be seen clearly from Figure 1.5, which separately illustrates the time trends in the average risk-return distances for both emerging and developed markets.

Although the risk-return characteristics of emerging markets have converged rapidly toward those of developed markets in recent years, the former still remains substantially different from the latter. For instance, as of the end of our sample period, i.e., the second 6-month period of 2004, the projected average risk-return distance for emerging markets is about 0.027. This distance is still more than three times as great as the average distance for developed markets (0.008) observed during the same period, i.e., the second 6-month of 2004, and about twice as great as the projected risk-return distance for developed markets (0.014) at the start of our sample period, i.e., the first 6-month period of 1974. In other words, emerging markets have a long way to go before a full convergence would be reached. Figure 1.5 indeed shows that if both

Table 1.8. Tests of the Convergence Hypothesis for 14 Emerging Markets

	Dependent Variable	Intercept(α)*100	Time(β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ statistic)
Cross-Market Average	risk-return distance	4.657	-0.061	-3.86***	0.281	-3.33***
	return distance	1.014	-0.013	-4.24***	0.234	-4.19***
	risk distance	2.725	-0.034	-3.13***	0.208	-3.53***
Cross-Market Median	risk-return distance	3.295	-0.033	-2.69**	0.153	-3.65***
	return distance	0.814	-0.012	-4.80***	0.252	-4.44***
	risk distance	1.459	-0.001	-0.09	0.000	-3.04***

emerging and developed markets maintain their respective speeds of convergence in the future, a full convergence of the former toward the latter may occur in around year 2022. However, if the pace of convergence slows down as markets become more integrated, a full convergence would take longer.

Table 1.9 presents the test results of the convergence hypothesis for individual emerging markets. For the risk-return distance measure (DRS), we reject the null hypothesis that there is no convergence for 4 out of 14 markets at the 10 percent level or better. The four emerging markets exhibiting a significant risk-return convergence toward developed markets are: Brazil, Chile, the Philippines, and Taiwan. In addition, six other markets (i.e., Argentina, Columbia, India, Mexico, Turkey, and Venezuela) exhibit a tendency to converge toward developed markets, albeit statistically insignificant. By contrast, four emerging markets, i.e., Jordan, Korea, Malaysia, and Thailand, exhibit a tendency to 'diverge' from developed markets in terms of risk-return characteristics, albeit statistically insignificant[20]. For the return distance (DR), we reject the null hypothesis of no convergence for 7 out of 14 markets at least at the 10 percent level[21]. For the risk distance (DS), on the other hand, we reject the null hypothesis of no convergence for 4 out of 14 markets at the 10 percent level or better.[22] One emerging market, Korea, exhibits a significant tendency to diverge from developed markets in terms of risk characteristic.

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[20] As is the case with developed markets, there is a strong negative relationship between the intercept and slope of the regressions for 14 emerging markets. Detailed results are available upon request.

[21] The seven markets are Brazil, Chile, Mexico, Philippines, Taiwan, Turkey, and Venezuela.

[22] The four markets are Argentina, Brazil, Chile, and Taiwan.

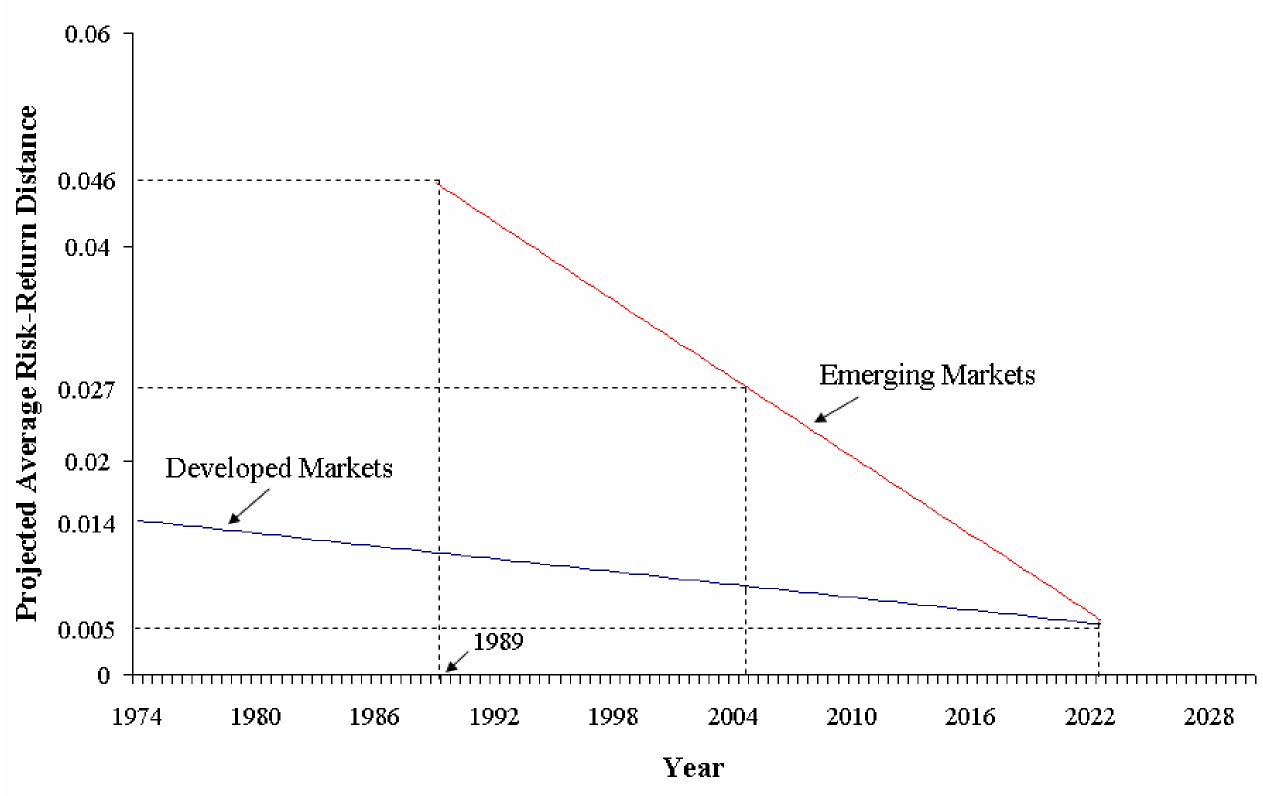

Figure 1.5. Time-Trend Projections of the Risk-Return Distances: Emerging vs. Developed Markets

To help us better understand the risk-return characteristics of emerging markets relative to those of developed markets, we plot the risk-return distances of both emerging and developed markets from the cross-market average of 17 developed markets for year 2003. As can be seen from Figure 1.6, developed markets cluster together rather tightly around the cross-market average. In addition, five emerging markets (Columbia, Malaysia, Mexico, Philippines, and Taiwan) are located within the inner circle in Figure 1.6, clustering closely with developed markets. But the rest of emerging markets are scattered far afield from developed markets in the risk-return space. Even though the risk-return characteristics of emerging markets have converged rapidly toward those of developed markets in recent years, many emerging markets remain very much different from developed markets in terms of risk-return characteristics. Consequently, emerging markets can still be viewed as a distinct asset class and may serve as an effective vehicle for international diversification, consistent with the recent finding by Goetzmann, Li, and Rouwenhorst (2005).[23] It is also pointed out that due to the data requirement, our sample emerging markets are all relatively seasoned such markets. As the next wave of emerging/nascent markets become available for international investors, emerging markets may continue to be an effective vehicle for international diversification.

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[23] Goetzmann, Li, and Rouwenhorst (2005) find that in recent years, the benefits from international diversification stem mainly from emerging markets.

Table 1.9. Tests of the Convergence Hypothesis for Individual Emerging Markets toward Developed Markets

Market	Risk-return distance					Return distance					Risk distance				
	Intercept (α)* 100	Time (β)* 100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ stat)	Intercept (α)* 100	Time (β)* 100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ stat)	Intercept (α)* 100	Time (β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ stat)
Argentina	10.434	-0.273	-1.54	0.185	-3.65***	1.497	-0.028	-0.96	0.052	-4.74***	8.148	-0.261	-2.05**	0.329	-3.07***
Brazil	9.412	-0.221	-4.20***	0.349	-2.83***	1.107	-0.020	-1.72*	0.054	-4.29***	6.755	-0.175	-4.58***	0.410	-4.96***
Chile	1.943	-0.037	-5.12***	0.216	-6.66***	0.756	-0.013	-3.15***	0.103	-6.23***	1.012	-0.020	-4.40***	0.131	-5.32***
Columbia	2.651	-0.035	-1.24	0.042	-4.93***	0.878	-0.007	-0.75	0.010	-6.16***	1.606	-0.030	-1.43	0.066	-4.26***
India	2.711	-0.029	-0.92	0.032	-6.33***	0.664	-0.001	-0.10	0.000	-6.66***	1.781	-0.032	-1.32	0.061	-3.47***
Jordan	1.311	0.009	0.79	0.014	-3.82***	0.425	-0.002	-0.65	0.004	-4.10***	0.632	0.014	1.36	0.050	-4.82***
Korea	2.395	0.076	1.11	0.049	-3.35***	0.813	0.002	0.12	0.001	-2.47**	0.990	0.080	1.95*	0.116	-2.96***
Malaysia	2.016	0.014	0.26	0.002	-3.16***	0.599	0.001	0.07	0.000	-3.91***	0.953	0.017	0.47	0.007	-3.60***
Mexico	3.184	-0.047	-1.13	0.073	-3.76***	0.937	-0.019	-3.30***	0.150	-6.04***	1.363	-0.005	-0.11	0.001	-2.63***
Philippines	3.411	-0.060	-1.99*	0.096	-3.31***	1.053	-0.020	-2.18**	0.079	-4.99***	1.889	-0.031	-1.63	0.049	-3.41***
Taiwan	5.119	-0.117	-2.87***	0.252	-5.69***	1.122	-0.028	-2.61**	0.156	-7.21***	3.182	-0.068	-2.16**	0.172	-4.05***
Thailand	3.027	0.035	0.62	0.014	-2.70***	0.774	0.012	0.78	0.017	-3.84***	1.718	0.028	0.66	0.167	-2.57**
Turkey	9.348	-0.087	-1.41	0.048	-6.65***	1.957	-0.034	-3.28***	0.154	-7.64***	5.129	0.005	0.10	0.000	-5.20***
Venezuela	6.025	-0.068	-1.42	0.033	-3.74***	1.609	-0.032	-1.90*	0.094	-6.05***	2.999	0.002	0.04	0.000	-5.43***
F-test (H_0: All β's = 0)	809.6***					10842.9***					874.5***				

Summary and Concluding Remarks

In this paper, we documented a significant risk-return convergence among a sample of 17 developed markets during the period 1974─2004. The speed of convergence, however, varies greatly across individual markets, mainly reflecting the initial distances of individual markets from the international average risk-return characteristic. We also showed that the risk-return convergence among developed markets is attributable to the declining country effect, rather than the rising industry effect. From this result, we infer that international financial integration may be the main driver of the risk-return convergence. As international capital markets have become more integrated, the idiosyncratic 'country' factor of individual markets may have become less important over time, resulting in the international convergence in risk-return characteristics.

We also found that the time trend, together with the world market volatility, substantially explains the dynamics of the risk-return distance over time. The risk-return distance shows no asymmetric behavior under bullish vs. bearish market conditions. We further showed that the increasing correlation among markets, an often cited trend, and the risk-return convergence documented in this study are related but distinct phenomena. Finally, we documented that the risk-return characteristics of emerging markets have rapidly converged toward those of developed markets in recent years. The recent convergence notwithstanding, the majority of emerging markets still remain substantially different from developed markets in terms of risk-return characteristics, supporting the view of emerging markets as a distinct asset class.

To conclude, our paper showed how the key characteristics of national stock markets have evolved in a systematic fashion as international financial markets have been moving toward a greater integration, stimulating cross-border financial flows and interactions.

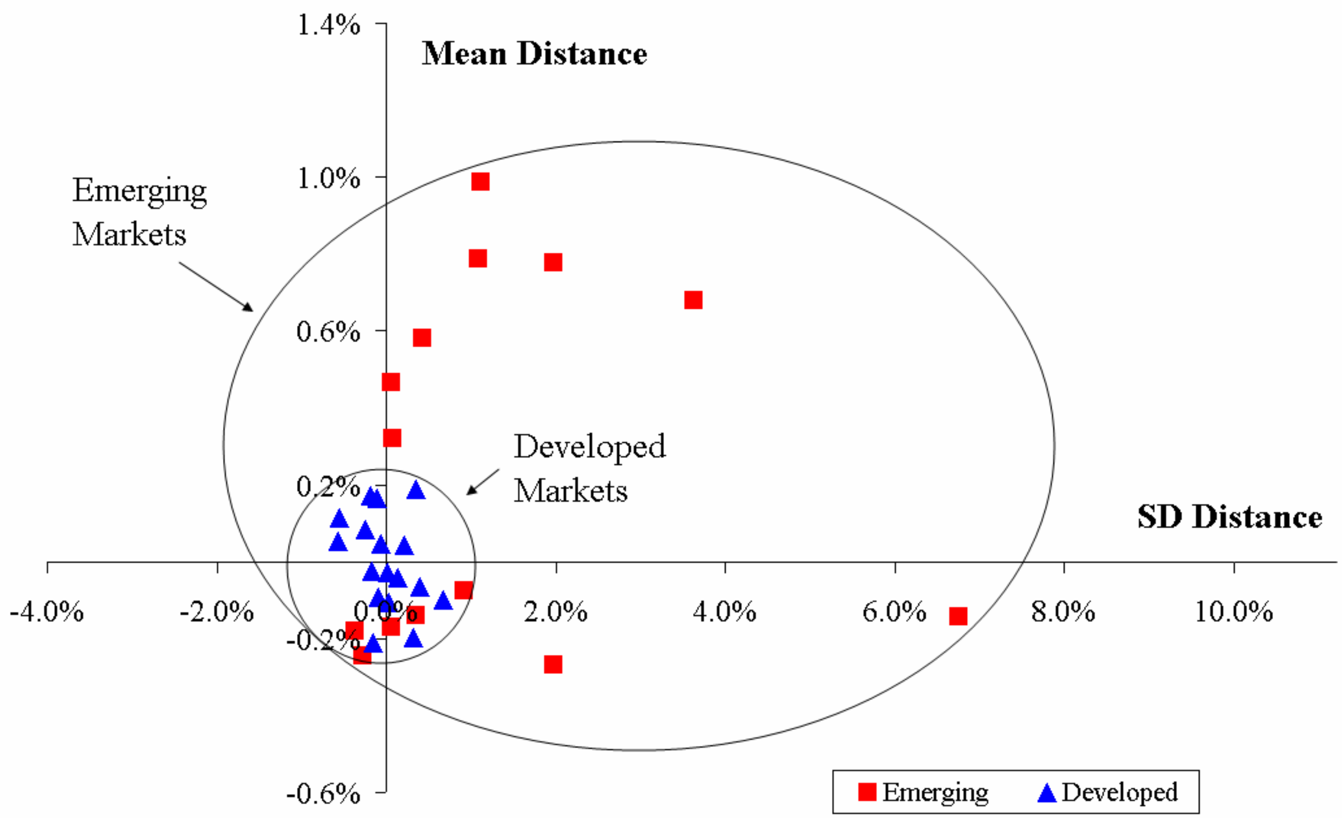

Figure 1.6. Risk-Return Distances from the Cross-Market Average of 17 Developed Markets for 2003: 17 Developed vs. 14 Emerging Markets

CHAPTER 2

EVOLUTION OF EARNINGS-TO-PRICE RATIOS: INTERNATIONAL EVIDENCE

Introduction

In this paper, we study the evolution of earnings-to-price ratios for 17 markets over the period from 1980 to 2004. Price-to-earnings ratio measures how much investors are willing to pay per dollar of current earnings, and some investors believe that a company with a higher price-to-earnings ratio is more likely to have higher growth opportunities or to be less risky. Thus, price-to-earnings ratio is often used in the market to evaluate a stock in reference to similar stocks in terms of risk and growth opportunities.

In this vein, previous research finds that price-to-earnings ratio is related to future stock returns and growth opportunities. For example, Campbell and Shiller (1988, 1998) study the S&P composite index since 1870s and find that the ratio of long-run moving average earnings to the current stock price is negatively correlated with future stock returns. Bekaert, Harvey, Lundblad, and Siegel (2005) use a country's industry weighted global price-to-earnings ratio and find that a measure of country-specific growth opportunities based on this ratio predicts future output and investment growth for a country.

There is another strand of literature where accounting aspect of earnings is emphasized. For example, French and Poterba (1991) argue that the price-to-earnings ratio for the Tokyo Stock Exchange would have been 32.6, not the reported 53.7, at the end of 1989 if Japanese firms used the U.S. accounting rules. In this spirit, Land and Lang (2002) document convergence in earnings-to-price ratios for sample firms from 7 developed markets over the period 1987 – 1999, and conclude that convergence in accounting practices is behind the convergence in international earnings-to-price ratios.

In this paper, we examine whether or not international earnings-to-price ratios converge toward each other and, if so, what explains the convergence in earnings-to-price ratio. Since the magnitude of price-to-earnings ratio is far larger than the corresponding earnings-to-price ratio[24], we use earnings-to-price ratio rather than price-to-earnings ratio in this study to reduce the impact of outliers on our analysis.

To tackle the issues in this study, we take a different approach from Land and Lang (2002). First, we use earnings-to-price ratio at the market level, not on firm level. By doing so, we can include more countries and longer period in our sample to examine the international evolution of earnings-to-price ratios. Thus, our sample consists of 17 markets during the period 1980 - 2004. Second, we explicitly introduce a distance measure, similar to the (dis)similarity measure in cluster analysis in order to quantify how much a market differs from the other markets in terms of earnings-to-price ratio. Our focus then is on whether there is a statistically significant downward time-trend in this measure, showing convergence in earnings-to-price ratios among international stock markets.

The key findings of our paper can be summarized as follows. First, earnings-to-price ratios for our sample of 17 markets have converged significantly toward each other during the period 1980 – 2004. Specifically, the projected cross-market average earnings-to-price distance

[24] Especially, the price-to-earnings ratio may explode as earnings approach zero.

and standard deviation among these markets has decreased by about 80% during the period, respectively.

Second, the speed of convergence varies greatly across individual markets and is closely related to the initial distance of individual markets from the international average: the farther away a market was initially from the international average, the more rapidly it converges toward the average.

Third, we examine which of two effects, industry or country, is the prime driver for the convergence in earnings-to-price ratio. Bekaert, Harvey, Lundblad, and Siegel (2005) argue that price-to-earnings ratio for an industry should be the same across countries if growth opportunities are priced in internationally integrated markets. If this is the case, there might be a convergence in earnings-to-prices ratio among our sample markets because these countries are integrated and the industrial structure across them has become more similar over time. To address this issue, we employ the Heston and Rouwenhorst (1994) method to generate two separate series of earnings-to-price ratios, one representing industry effect and the other country effect, and conduct the convergence tests separately with each of the two series. Our results show that although both country and industry effects account for convergence in earnings-to-price ratios among the sample markets, country effect dominates industry effect in terms of the magnitude of each effect on convergence in earnings ratio. Thus, we conclude that the convergence in earnings-to-price ratio is mainly attributable to the declining country effect. Fourth, we further examine what might explain the declining country effect. Especially, we consider whether or not the declining country effect could be explained by the convergence in international accounting practices as suggested by Land and Lang (2002). For this purpose, we introduce dividend-yield distance, which is defined in the same way as earnings-to-price distance, and find that dividend-yield distance exhibits similar time trend as earnings-to-price distance for the sample markets. Dividends are actually paid out to shareholders. Thus, if the level of earnings changes due to changes in accounting practices, changes in earnings are not likely to result in changes of dividends. On the other hand, if the level of earnings changes due to economic factors, changes in earnings probably end up with changes in dividends. Our results clearly show that the time trend of dividend-yield distance measure closely follows that of earnings-to-price distance measure. However, the payout-ratios of sample markets do not show any trend over the period. Overall, these results suggest that convergence in earnings-to-price ratio over the sample period is mainly due to convergence in economic factors such as growth opportunities or discount rates, rather than due to convergence in accounting practices. The rest of the paper is organized as follows. Section 2 describes the data and methodology. Section 3 provides tests of the convergence among our sample stock markets. Section 4 discusses the driver of the convergence in earnings-to-price ratio. Section 5 provides summary and concluding remarks.

Data and Methodology

Data

The primary data for this study are monthly earnings-to-price ratios for 17 markets over the period from 1980 through 2004. We start our sample period in 1980 because a rapid

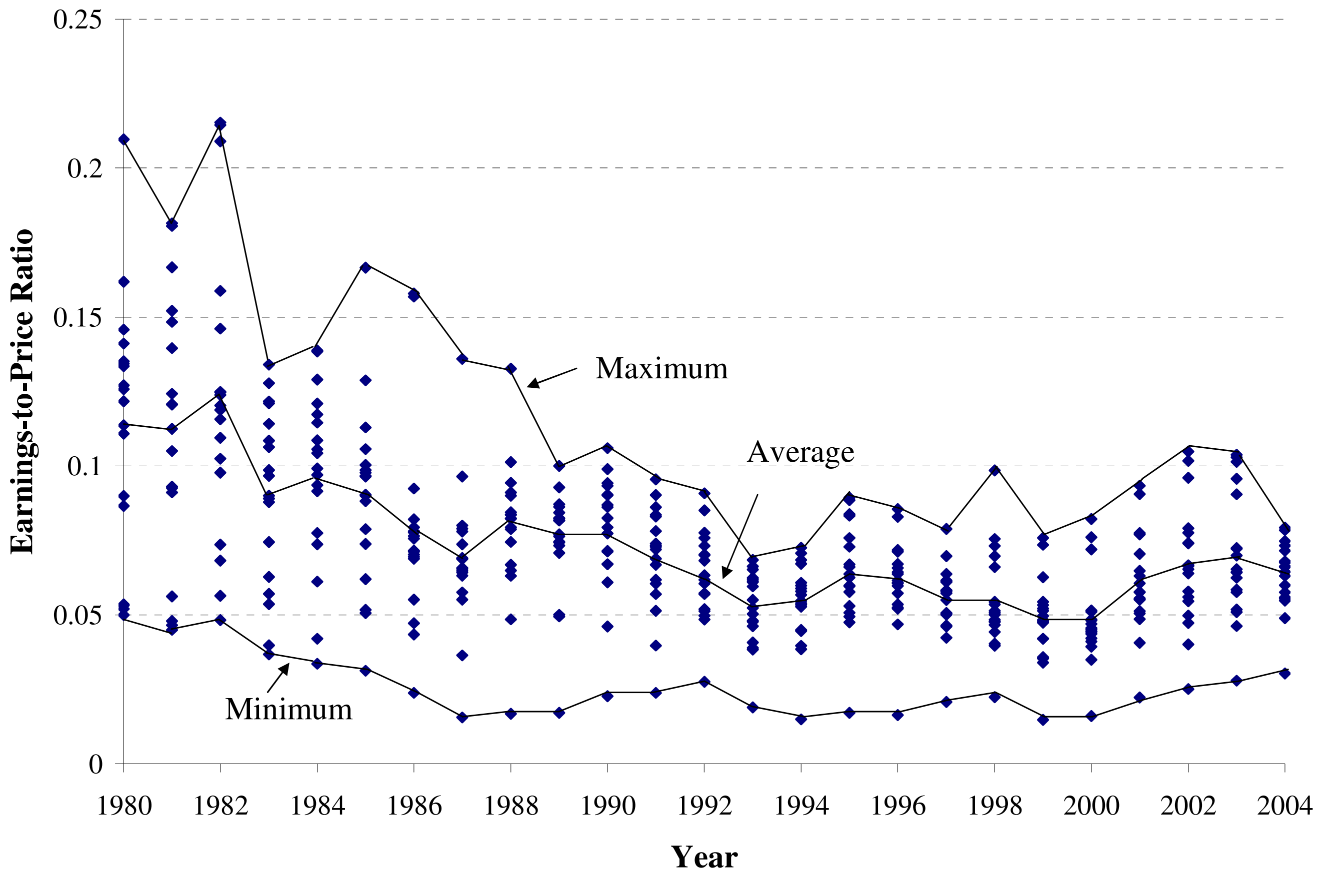

Figure 2.1. Earnings-to-Price Ratios for 17 Markets, 1980 – 2004

integration of international capital markets has occurred since 1980s[25]. The 17 markets in our sample are Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Ireland, Japan, the Netherlands, Norway, Singapore, South Africa, Switzerland, the United Kingdom, and the United States. These markets are selected because of the data availability. They are the markets for which the data on the earnings-to-price ratios are available from the DataStream since 1980. Earnings-to-price ratio for a market index is computed by dividing the total earnings of the index constituents by the total market value for those constituents. Thus, earnings-to-price ratio for a market index is regarded as a value-weighted average of earnings-to-price ratios of the index constituents.

Table 2.1 provides descriptive statistics for the DataStream country indices in our sample at the end of 1980, 1992 and 2004 respectively. More stocks are included in each index over time. For example, 491 stocks were included for the U.S. index in 1980. The corresponding numbers in 1992 and in 2004 were 738 and 995 respectively. The U.S. is the largest market in terms of the market capitalization. Japan and the U.K. follow. For earnings-to-price ratio, there is a substantial cross-market variation each year. However, the magnitude of the variation becomes consecutively smaller over these three years. At the end of 1980, the range between the highest and lowest earnings-to-price ratios was 14.7 percent (highest: 18.9 percent for Hong Kong, lowest: 4.2 percent for Austria). The corresponding numbers at the ends of 1992 and 2004 were

[25] Consistent with this view, Mittoo (1992) documents that the stock markets for Canada and the U.S. were segmented during the period 1977 – 1981, but that they became integrated during the period 1982 - 86. Gultekin, Gultekin, and Penati (1989) report that the U.S. and Japanese stock markets became integrated after the elimination of capital controls in Japan in 1980. For a review on the international asset pricing theories and empirical studies, refer to Karolyi and Stulz (2002).

Table 2.1. Descriptive Statistic for Stock Market Country Indices for 17 Countries

Country	1980			1992			2004		
	Number of Stocks	Market Capitalization ($ Billions)	Earnings-to-Price Ratio	Number of Stocks	Market Capitalization ($ Billions)	Earnings-to-Price Ratio	Number of Stocks	Market Capitalization ($ Billions)	Earnings -to-Price Ratio
Australia	49	29.1	0.085	106	99.3	0.049	155	641.5	0.056
Austria	12	0.5	0.042	33	13.8	0.055	50	87.4	0.058
Belgium	28	6.0	0.143	59	44.6	0.075	89	268.7	0.068
Canada	78	46.3	0.122	176	168.1	0.044	250	963.9	0.056
Denmark	20	2.5	0.104	36	21.9	0.061	50	142.7	0.062
France	62	25.8	0.132	148	231.2	0.077	247	1,435.8	0.076
Germany	85	55.7	0.110	153	271.1	0.058	249	1,117.4	0.076
Hong Kong	36	25.0	0.045	91	125.4	0.083	130	706.1	0.061
Ireland	19	1.4	0.156	41	10.1	0.071	50	106.1	0.065
Japan	542	304.5	0.052	874	2,145.8	0.025	1000	3,485.8	0.036
Netherlands	62	25.4	0.189	94	142.7	0.078	127	612.2	0.084
Norway	12	2.1	0.139	34	11.4	0.068	50	137.3	0.059
Singapore	19	5.6	0.043	76	42.0	0.053	99	153.8	0.074
South Africa	15	25.8	0.141	44	74.1	0.076	69	225.1	0.072
Switzerland	55	15.7	0.088	115	103.5	0.066	149	811.9	0.063
U.K.	259	128.1	0.132	411	713.6	0.056	548	2,727.8	0.066
U.S.	491	685.0	0.115	738	3,032.4	0.050	995	13,345.4	0.049
Cross-Market Average			0.108			0.061			0.064
Cross-Market STD			0.042			0.015			0.011

5.8 percent (highest: 8.3 percent for Hong Kong, lowest: 2.5 percent for Japan) and 4.8 percent (highest: 8.4 percent for the Netherlands, lowest: 3.6 percent for Japan), respectively.

Figure 2.1 shows the evolution of the earnings-to-prices ratios for 17 markets for the period 1980 – 2004. There are some notable trends in the Figure 2.1. Although there are fluctuations, the range between the highest and lowest earnings-to-price ratios becomes smaller over time, especially up to the early 1990s. The highest ratio declines more than the lowest one, and the average ratio also declines over time.

Methodology

To test the convergence in earnings-to-price ratios for 17 markets, we introduce two measures related to the dispersion of earnings-to-price ratios for markets.

The first measure is a distance measure, which is similar in concept to the (dis)similarity measure used in cluster analysis. One of the most popular methods to measure (dis)similarities in cluster analysis is the Euclidean distance. The smaller the Euclidean distance between the observations, the more similar they are.

To apply the (dis)similarity measure in cluster analysis, we calculate the earnings-to-price distance (EP distance hereafter) for a particular market as the Euclidean distance between (i) earnings-to-price ratio for a market and (ii) the cross-market average of earnings-to-price ratios for N markets. For each market, we compute the EP distance for each observation period. Specifically, the EP distance for market i during the period t (DEP_{it}) is computed as follows:

$$DEP_{it} = \left| EP_{it} - \frac{1}{N}\sum_{i=1}^{N} EP_{it} \right|, \quad i = 1, \ldots, N; \; t = 1, \ldots, T \qquad (1)$$

where EP_{it} is the earnings-to-price ratio for market i during the period t.

Table 2.2. Cross-Market Average of the EP Distance Measures and Standard Deviation of Earnings-to-Price Ratios for 17 Markets

Year	Semi-annual period	Cross-Market Average of the Distance Measure (%)	Cross-Market Standard Deviation (%)	Year	Semi-annual period	Cross-Market Average of the Distance Measure (%)	Cross-Market Standard Deviation (%)
1980	1	3.70	4.52	1993	1	1.11	1.37
	2	3.45	4.44		2	1.02	1.28
1981	1	3.84	4.66	1994	1	0.99	1.32
	2	3.77	4.64		2	1.12	1.58
1982	1	4.25	5.75	1995	1	1.36	1.87
	2	3.84	4.89		2	1.38	1.79
1983	1	2.85	3.60	1996	1	1.07	1.57
	2	2.54	2.96		2	1.01	1.53
1984	1	2.16	2.68	1997	1	0.88	1.33
	2	2.69	3.62		2	1.00	1.32
1985	1	2.48	3.33	1998	1	1.24	1.74
	2	2.15	3.12		2	1.41	1.87
1986	1	2.08	3.27	1999	1	1.13	1.53
	2	2.23	3.72		2	1.00	1.44
1987	1	1.65	2.63	2000	1	1.10	1.56
	2	1.52	2.42		2	1.10	1.63
1988	1	1.63	2.60	2001	1	1.25	1.72
	2	1.63	2.31		2	1.39	1.93
1989	1	1.34	1.93	2002	1	1.42	1.84
	2	1.35	2.05		2	2.04	2.53
1990	1	1.58	2.11	2003	1	2.02	2.53
	2	1.62	2.09		2	1.50	1.92
1991	1	1.50	1.89	2004	1	1.04	1.36
	2	1.38	1.88		2	0.85	1.16
1992	1	1.23	1.71	Average		1.78	2.40
	2	1.25	1.54				

Once we have the EP distance for each market according to Equation (1), we compute the cross-market average (or median) of the EP distance measures for N markets for each period. We then check if there is any time trend in the cross-market average (or median) EP: If the cross-market average (or median) EP distance shows a downward (upward) time trend, we infer that the earnings-to-price ratios for N markets converge toward (diverge from) each other over time.

As the second measure to study the convergence in earnings-to-price ratio, we use the σ-convergence, which has been used in the economic growth literature[26]. In a study of convergence in economic growth across the United States and European regions, Barro and Sala-i-Martin (1991) introduced the notion of σ-convergence. In their study, σ-convergence occurs when the cross-sectional standard deviation of per capita income among regions diminishes over time. Under this definition, in our study, diminishing cross-sectional standard deviation of earnings-to-price ratios for our sample markets over time can be regarded as evidence of convergence in earnings-to-price ratios.

Evolution of Earnings-to-Price Ratios for 17 Markets

Time Trend in the EP Distance Measures

Table 2.2 reports the cross-market average of the EP distance measure and the standard deviation of earnings-to-price ratios for each semi-annual period. We use the mean of six monthly earnings-to-price ratios for each market as the earnings-to-price ratio for the market during the six-month period. Then, we compute the cross-market average EP distance and the standard deviation of earnings-to-price ratios among sample markets for each six-month period. During our sample period 1980-2004, the average EP distance is 1.78%, whereas the average standard deviation is 2.40%. The average EP distance means that the absolute difference between

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[26] For the literature review on growth economics and concepts of convergence in the literature, refer to Durlauf and Quah (1999).

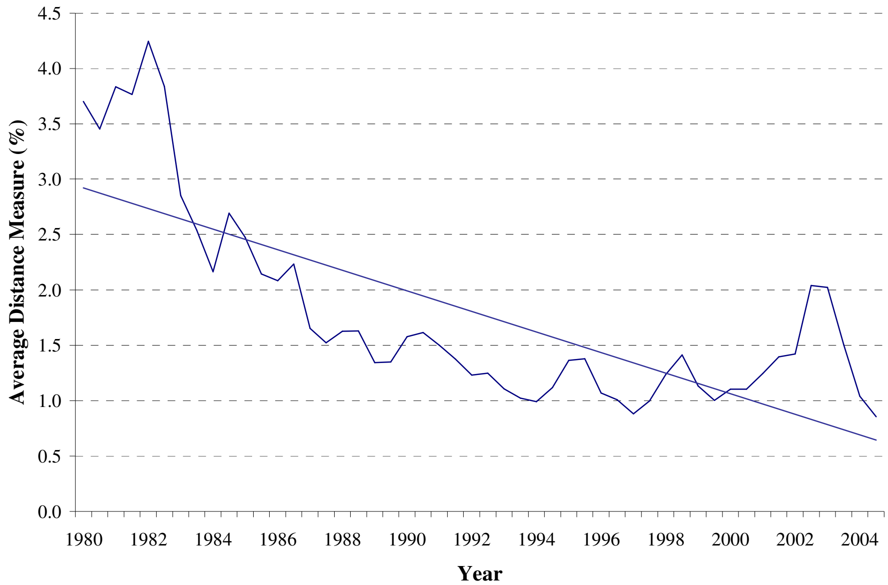

Figure 2.2. Time Trend in the Cross-Market Average of EP Distances for 17 Markets

earnings-to-price ratio for a representative market and the cross-market average earnings-to-price ratio is 1.78% during our sample period.

Figure 2.1 plots cross-market average EP distance measure, and Figure 2.3 shows the standard deviation of earnings-to-price ratios over time. Figure 2.2 and Figure 2.3 clearly show that there is a downward trend both in the average EP distance measure and in the standard deviation of earnings-to-price ratios, respectively.

Tests of the Convergence Hypothesis

To test if there is a time trend in the EP distance measures (DEP_t) or in the standard deviation (STD_t) of earnings-to-price ratios, we run the following regression and see if the time coefficient is significantly different from zero:

$$DEP_t \text{ (or } STD_t) = \alpha + \beta \text{ Time } + \varepsilon_t, \text{ Time} = 1, \dots, 50 \quad (2)$$

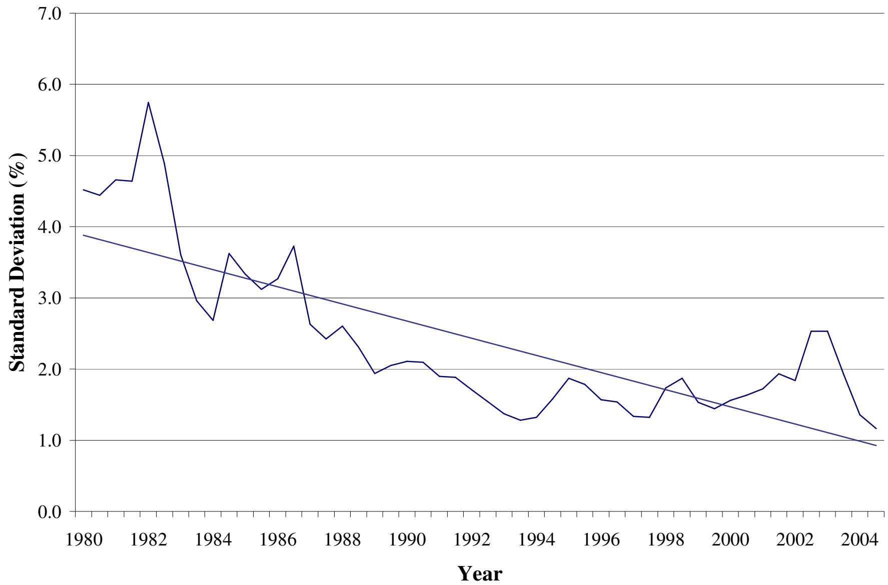

Figure 2.3. Time Trend in the Cross-Market Standard Deviation of Earnings-to-Price Ratios for 17 Markets

When we examine if a variable has a time trend, a relevant procedure depends on the property of error term. If the error term is stationary, the standard test can be applied. However, if the error term is not stationary, the statistic from the standard test is not reliable. Therefore, we first examine if our sample has errors with a unit root. For this purpose, we employ the augmented Dickey-Fuller (ADF) test. The null hypothesis of the ADF test is that errors from a time trend model have a unit root with no constant or no

Table 2.3. Tests of the Convergence in Earnings-to-Price Ratios for 17 Markets, 1980 – 2004

Dependent Variable	Intercept	Time	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ statistic)
Cross-Market Average Distance Measure	0.02967	-0.00046	-3.19***	0.569	-2.01**
Cross-Market Median Distance Measure	0.02329	-0.00038	-2.24**	0.400	-3.62***
Cross-Market Standard Deviation	0.03936	-0.00060	-3.85***	0.609	-2.27**

time trend[27]. If the null hypothesis of the ADF test is rejected, we conclude that the statistic from a standard test is likely to be valid. For a standard test, coefficients are estimated by the Newey-West heteroskedastic autocorrelation consistent estimation with a lag of 6. The t_{HAC} is the Newey-West t-statistic computed by the estimation.

Table 2.3 reports test results for the convergence in earnings-to-price ratios for 17 markets. For each case, the ADF test rejects the null hypothesis that errors have a unit root at the 5 percent significance level or better and thus the standard test is applied for the convergence test. For each case, the coefficient of time variable is negative and its Newey-West t-statistic is statistically significant at least at the 5 percent level. Therefore we infer that the earnings-to-price ratios for 17 sample markets have converged toward each other over our sample period.

The convergence for earnings-to-price ratios is also economically substantial. The intercept of the regression can be interpreted as the estimated 'initial' EP distance from the cross-market average, whereas the slope may be interpreted as the speed of convergence toward the cross-market average. In Table 2.3, when we use the cross-market average distance measure, we infer that the projected initial EP distance is 0.02967 (or 2.967 percent). On the other hand, the projected EP distance from the cross-market average for the last six-month period, i.e., the second semi-annual period of 2004,

[27] The number of lags for the ADF test is determined by the method recommended in Campbell and Perron (1991). The maximum lag we consider is 6. The order of lag is reduced by one until the coefficient on the last included lag is significant at the 10 percent level.

is 0.00667 (or 0.667 percent). Therefore, during our sample period, the projected EP distance from the cross-market average has decreased by about 80 percent for our sample markets. We come to the similar conclusion when we use either the cross-market median distance measure or cross-market standard deviation.

Next, we check if the convergence in earnings-to-price ratio is robust to controlling for a variable representing the macro economic condition. Lamont (1998) argues that the level of earnings predicts future returns because the level of earnings is a measure of current business condition. In this case, EP distance might varies with business conditions and this might affect our conclusion. To check this possibility, we use the NBER (National Bureau of Economic Research) business cycle as a proxy for the world macroeconomic condition[28]. Down is a dummy variable, which takes the value of one if any semi-annual period has at least 3 months in the 'contraction' period defined by the NBER. Since there might be time lead or lag between accounting income and macroeconomic condition, we also assign the value of one to the two adjacent semi-annual periods to the contracted semi-annual period as defined above. The value of zero is assigned to other periods.

Table 2.4 reports the test results of the convergence in the EP distance measure for 17 markets under different macroeconomic conditions. The cross-market average (or median) EP distance measure or the cross-market standard deviation of earnings-to-price ratios for 17 markets is regressed on the time variable and the down dummy variable. For

[28] The expansion and contraction periods of the U.S. business cycle are available in the NBER website (http://www.nber.org/cycles.html).

Table 2.4 Tests of the Convergence in Earnings-to-Price Ratios for 17 Markets under Different Economic Conditions, 1980 – 2004

Dependent Variable	Intercept	Time	t_{HAC} (Time)	Down	t_{HAC} (Down)	R^2	Unit Root Test for Residuals (τ statistic)
Cross-Market Average Distance Measure	0.02646	-0.00041	-4.24***	0.00616	2.28**	0.662	-1.71*
Cross-Market Median Distance Measure	0.01961	-0.00032	-2.61**	0.00704	2.18**	0.525	-2.65***
Cross-Market Standard Deviation	0.03607	-0.00055	-5.11***	0.00631	1.99*	0.609	-2.67***

each case, the time coefficient is still negative and significant at the 5 percent level or better, confirming the convergence in earnings-to-price ratio during our sample period. The coefficient on the dummy variable is positive and significant at least at the 10 percent level, suggesting that the EP distance becomes greater when the market experiences contraction in economic activity.

Now we discuss the issue of the convergence at the individual market level. Table 2.5 presents the test results of the convergence in the earnings-to-price ratio for 17 individual markets. Since the ADF test rejects the null hypothesis that error has a unit root at least at the 10 percent significance level for each market, we apply the standard test with the Newey-West t-statistic. For the EP distance measure, we can reject the null hypothesis that there is no convergence in earnings-to-price ratio over time at the 10 percent level or better for 12 out of 17 markets[29]. This result implies that the convergence in earnings-to-price ratios among our sample stock markets is not driven by a few outlier markets.

However, there is one major exception, the U.S., where we observe a statistically significant tendency to diverge from the rest of the markets. Figure 2.4 plots the earnings-to-price ratio for the U.S. and the cross-market average earnings-to-price ratio for the other 16 markets over time. The two ratios show a similar trend before 1995, but clearly diverge afterwards. Figure 2.5 shows the proportion of earnings for the U.S. to those for the world and the market capitalization for the U.S. to that for the world. The proportion of earnings for the U.S. has been around 40 percent since the early 1990s,

[29] The twelve markets are Austria, Canada, Denmark, France, Germany, Hong Kong, Ireland, Japan, the Netherlands, Norway, Singapore, and the United Kingdom.

Table 2.5. Tests of the Convergence in Earnings-to-Price Ratios for Individual markets toward the Cross-Market Average, 1980 – 2004

Market	Intercept	Time	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ statistic)
Australia	0.01035	-0.00007	-0.51	0.022	-2.43**
Austria	0.04461	-0.00082	-3.22***	0.477	-3.02***
Belgium	0.00873	0.00018	0.78	0.052	-1.94*
Canada	0.01715	-0.00026	-1.91*	0.164	-4.16***
Denmark	0.02903	-0.00050	-2.90***	0.164	-3.72***
France	0.01579	-0.00022	-1.92*	0.141	-3.33***
Germany	0.02400	-0.00044	-1.76*	0.227	-2.94***
Hong Kong	0.03567	-0.00067	-2.52**	0.330	-2.64***
Ireland	0.04060	-0.00083	-2.27**	0.309	-2.05**
Japan	0.06522	-0.00070	-7.12***	0.656	-4.48***
Netherlands	0.03871	-0.00085	-2.66**	0.414	-2.09**
Norway	0.06036	-0.00106	-4.00***	0.342	-4.42***
Singapore	0.05685	-0.00128	-5.96***	0.757	-1.78*
South Africa	0.03041	-0.00035	-0.81	0.060	-1.97**
Switzerland	0.01239	-0.00010	-0.95	0.062	-3.84***
U.K.	0.01175	-0.00019	-1.96*	0.166	-2.20**
U.S.	0.00274	0.00028	2.46**	0.324	-3.77***

whereas the proportion of the market capitalization for the U.S. shows a tendency to increase during the 1990s. The proportion of the market capitalization for the U.S. has been higher than the proportion of earnings for the U.S since the late 1990s. This suggests that the unusual result for the U.S. is due to the relatively booming stock market for the U.S. during the 1990s.

Factors Related to the Speed of Convergence

It is notable from Table 2.5 that the intercept and the slope coefficient seem to be correlated across markets. Indeed Figure 2.6 shows that there is a strong negative relationship between the intercept and slope of the regressions for 17 markets. As we discussed, the intercept of the regression may be interpreted as the estimated initial EP distance from the cross-market average earnings-to-price ratio, whereas the slope can be interpreted as the speed of convergence toward the cross-market average. To be precise, the speed of convergence is the negative of the slope, i.e., $(-1)\beta$.

Thus, the strong negative relationship between the intercept and slope suggests that the speed of the convergence toward the cross-market average is higher when the initial EP distance from the cross-market average is greater. For markets with a relatively high level of initial EP distance from the cross-market average such as Norway and Singapore, the speed of convergence is relatively high. On the other hand, for markets with a relatively low level of initial EP distance such as France and the U.K., the speed of convergence toward the cross-market average is also relatively low. Some markets, such as Australia, Belgium and Switzerland, that are located near the cross-market average do not show a significant time trend.

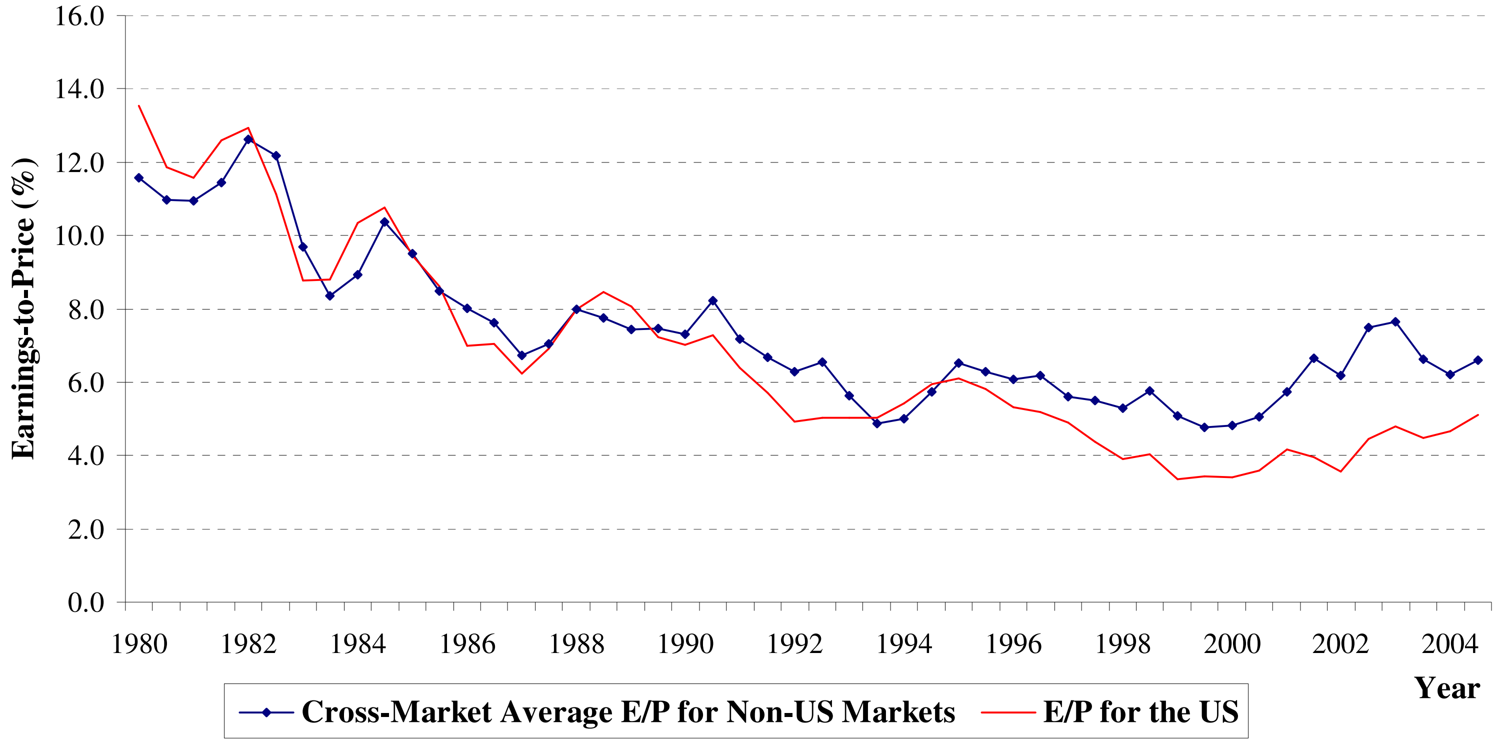

Figure 2.4.. Time Trend in the Earnings-to-Price Ratio for the U.S.

Next, we examine what other factors may be related to the speed of convergence. We consider the size of equity market, a dummy variable for common law, return convergence, convergence in corporate tax rate and GDP growth rate.

We conjecture that smaller markets may adjust more than larger markets as markets become integrated. We calculate the mean equity market capitalization of each market during the sample period and use the natural logarithm of the mean equity market capitalization as the size of the market. We collect the data on equity market capitalization through the DataStream.

Ball, Kothari, and Robin (2000) find that there is systematic difference in accounting incomes between common-law and code-law countries. Accounting income in common-law countries is more timely[30] than in code-law countries, due to quicker incorporation of economic losses. Choi and Meek (2005) point out that the International Accounting Standard Board (ISAB), which represents accounting organizations from about 100 countries and is the driving force in international accounting standard setting, has issued International Accounting Standards (IAS) which are closely compatible with accounting standards in common-law countries such as the U.S. and the U.K. Thus, combined with Ball, Kothari, and Robin (2000) and Choi and Meek (2005), we conjecture that earnings-to-price ratios for code-law countries may adjust more toward those for common-law countries through convergence in accounting practices. To address this possibility, we introduce a dummy variable of common-law, which takes a

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[30] Ball, Kothari, and Robin (2000) define timeliness as “the extent to which current-period accounting income incorporates current-period economic income.”

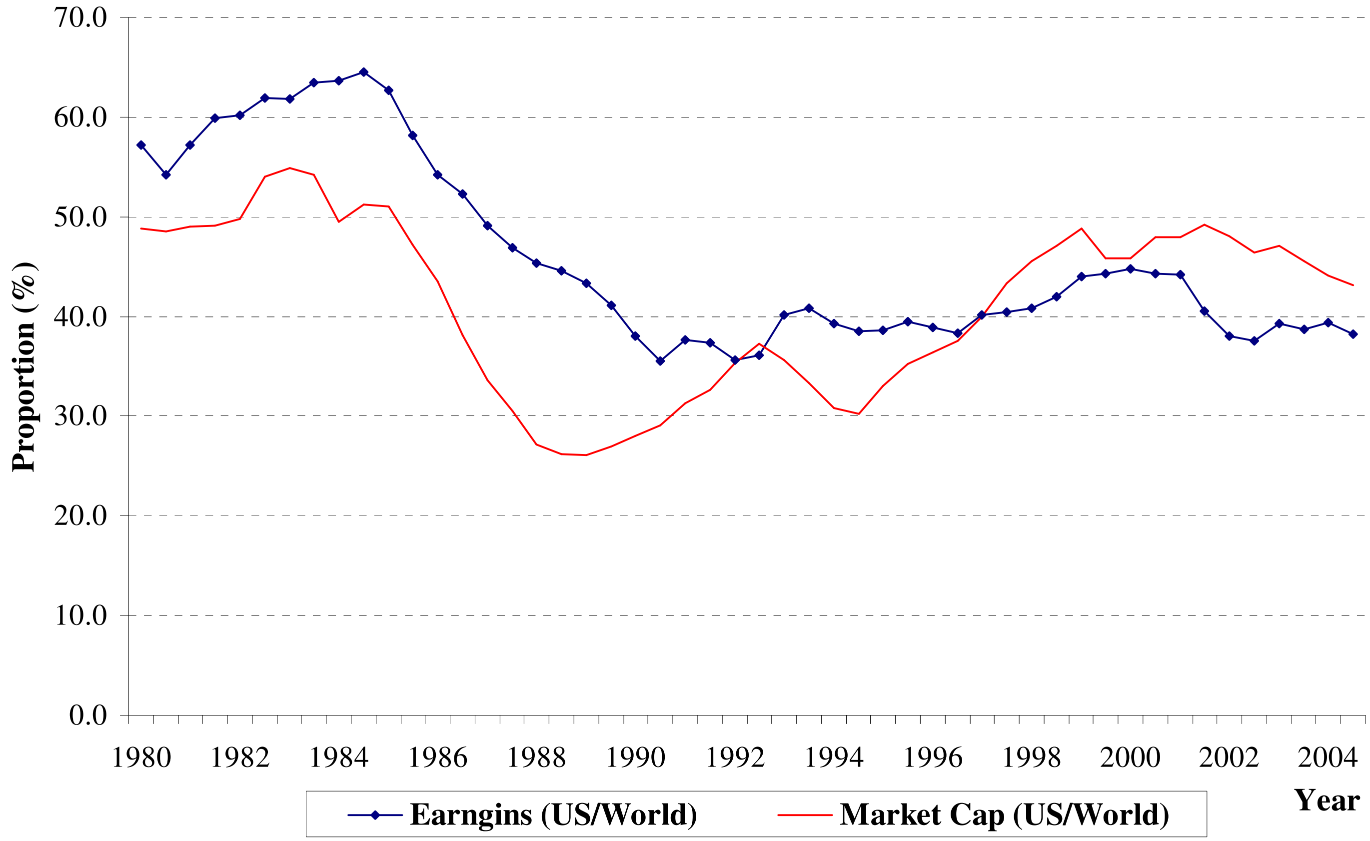

Figure 2.5. Time Trend in Earnings and the Market Capitalization for the U.S

value of one if a market is classified as a common-law country and zero otherwise[31]. The information on the legal system for each country is gathered from the World Factbook published by the U.S. governmental agency[32].

There is an extensive literature in accounting area on the relationship between earnings and stock returns[33]. To take into account the possible relationship between earnings and stock returns, we introduce return distance measure similar to the EP distance measure and compute the speed of return convergence toward the cross-market average return. More specifically, for each semi-annual period, return distance for a market is computed by the absolute difference between the mean of weekly returns for the market and the cross-market average of mean weekly returns for 17 markets. Then we run a time regression similar to that in section 3.2 and take the time coefficient as the speed of return convergence toward the cross-market average return. We expect that the speed of convergence in earnings-to-price ratio for a market is higher when the speed of convergence in returns for the market is higher. The data on returns for 17 markets are collected through the DataStream.

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[31] Among seventeen countries in our sample, eight countries are categorized as common-law countries. Those countries are Australia, Canada, Hong Kong, Ireland, Singapore, South Africa, the United Kingdom, and the United States.

[32] The on-line version of the World Factbook is available at 'http://www.cia.gov/cia/publications/factbook/'.

[33] For a literature review on this issue, refer to Kothari (2000) and the reference therein.

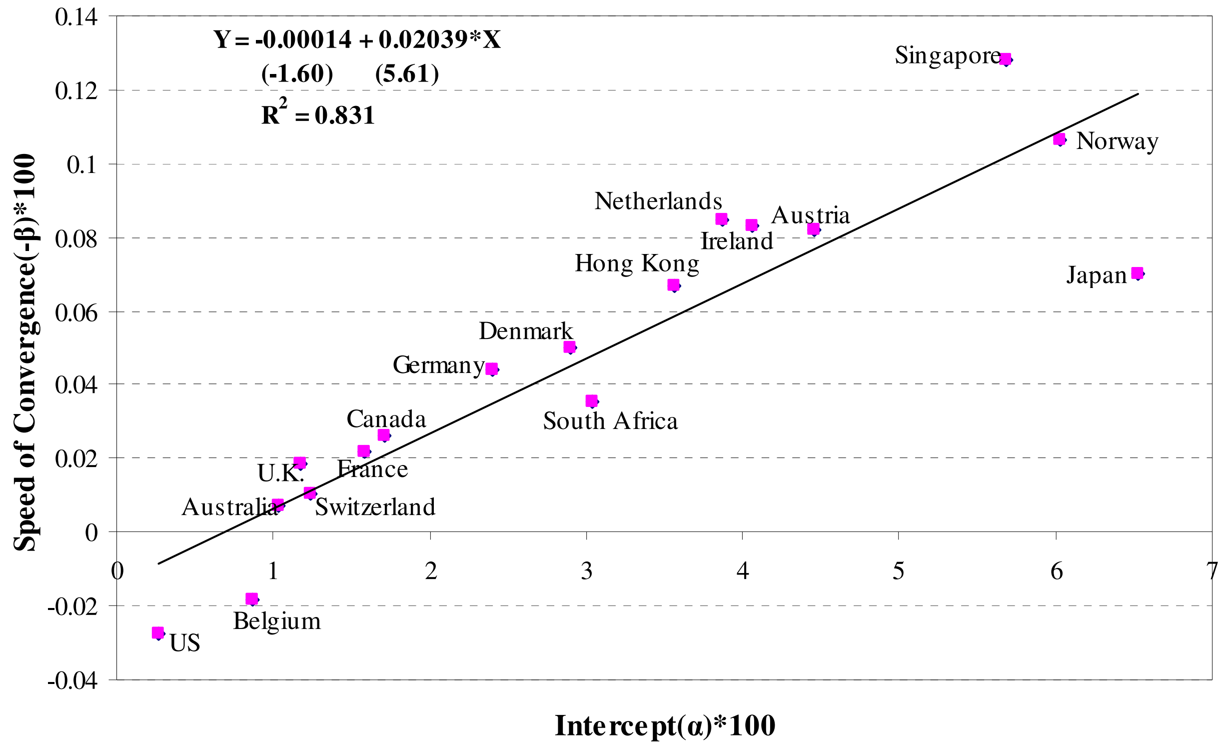

Figure 2.6. Relationship between the Intercept and Slope of Time Trend Regression of the EP Distance Measure

The next variable we consider is corporate tax rate. Since earnings are computed on after-tax basis, changes in corporate tax rate would directly affect level of earnings. However, since changes in earnings would entail changes in price, the effect of corporate tax rate on earnings-to-price ratio is a priori unclear. Thus, it is an empirical issue whether or not convergence in corporate tax rate would result in convergence in earnings-to-price ratios. We use top marginal tax rate on corporations as a representative tax rate for each country. The information on top marginal corporate tax rate is collected through the World Tax Database[34] maintained by the University of Michigan and is supplemented through the World Development Indicators published by the World Bank.

We also consider the speed of convergence in the GDP growth as an additional explanatory variable. Guenther and Young (2000) document that financial accounting earnings are associated with real economic activity[35]. Thus, we include the speed of convergence in the GDP growth rate as an additional variable to possibly explain the speed of convergence in earnings-to-price ratios. The data on GDP for 17 countries are also collected through the DataStream.

The last variable we consider is inflation. French and Poterba (1991) argue that inflation is a source of differences between accounting and economic earnings. For example, true depreciation costs are understated since depreciation is computed with the historical cost of assets. Thus, profits are overstated in periods of high inflation, which

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[34] The database is available on-line at 'http://www.bus.umich.edu/OTPR/otpr/introduction.htm'.

[35] They find that the association between financial accounting earnings and real economic activity is high for common-law countries such as the U.S and the U.K. and that the association is low for code-law countries such as France and Germany.

makes earnings-to-price ratio higher. This implies that the smaller the difference in inflation between countries, the less the difference in earnings-to-price ratio between them. The data on inflation for 17 countries are gathered from the International Financial Statistics published by the International Monetary Fund.

For corporate tax rate and GDP growth rate, similarly to the above procedure, we compute the absolute difference between the GDP growth rate (corporate tax rate) for a country and the cross-country average of GDP growth rates (corporate tax rates) for 17 markets every year. Then we run a time regression similar to that in section 3.2 and take the time coefficient as the speed of return convergence toward the cross-market average GDP growth rate (corporate tax rate).

Table 2.6 reports the regression results for factors related to the speed of convergence in earnings-to-price ratios. The dependent variable in each regression is the speed of convergence (-β) from the EP convergence tests for individual markets in Table 2.4. It is noted that the speed of convergence is the negative of the estimated slope, i.e., (-1)β. The heteroskedasticity-robust t-values are reported within parentheses. In model 1, we regress the speed of convergence (-β) on the intercept (α) from the EP convergence tests in Table 2.4. As we already mentioned, there is a strong negative relationship between the intercept and the speed of convergence. The coefficient of the intercept is positive (t-statistic of 5.61) and significant at the 1 percent level[36]. In model 2, we regress

[36] When we estimate intercept and slope from a regression, there is a negative correlation between these two estimates. Thus, we cannot rule out the possibility that the negative relationship between these two estimates might be an artifact from this statistical property. To take this possibility into account, we regress the speed of convergence on the mean of

the speed of convergence on the market size. The coefficient of the market size is significantly negative at the 5 percent level, implying that smaller markets indeed converge faster than larger markets. In model 3, 4, 5, 6, and 7 where we regress the speed of convergence on the common law dummy, the time trend of return distance, the time trend of corporate tax rate, the time trend of GDP growth rate, and the time trend of inflation respectively, none of the coefficients are significant. In model 8, we include market size, common law dummy, and trends of return distance, corporate tax rate, GDP growth, and inflation. The market size becomes insignificant and none of the variables is significant in this model. In model 9, we have all the independent variables together and find that the intercept (α) is the only significant variable.

Overall, we conclude that the projected initial risk-return distance from the international average strongly influences the speed of convergence toward the international average.

What Drives Convergence in Earnings-to-Price Ratios for 17 Markets

In this section, we examine which of two effects, industry or country, is the prime driver for the convergence in earnings-to-price ratio. Then, we further examine what could explain the declining country effect.

Industry versus Country Effects

Bekaert, Harvey, Lundblad, and Siegel (2005) argue that price-to-earnings ratio for an industry should be the same across countries if growth opportunities are priced in

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'actual' distance measures over the first two years, instead of the estimated intercept. In this case, the coefficient of the actual distance measure is still significantly positive (t-statistic of 5.31) at the 1 percent level, with a R-square value of 0.628

Table 2.6. Factors Related to the Slope from the Convergence Tests for Individual Markets

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
	Dependent Variable = Speed of Convergence ($-\beta$) from the Convergence Test								
Constant	-0.00014 (-1.60)	0.00211 (2.99)***	0.00050 (3.73)***	0.00034 (2.09)*	0.00043 (3.07)***	0.00048 (4.64)***	0.00033 (1.80)*	0.00111 (0.58)	-0.00039 (-0.54)
Intercept (α) from the Convergence Test	0.02039 (5.61)***								0.01913 (6.44)***
Log (Market Cap)		-0.00014 (-2.36)**						-0.00008 (-0.69)	-0.00001 (-0.01)
Common Law Dummy			-0.00008 (-0.36)					-0.00001 (-0.00)	0.00010 (1.02)
Trend (Return)				-2.74547 (-1.09)				-2.74965 (-0.38)	-3.08130 (-1.19)
Trend (Corporate Tax Rate)					-0.00020 (-0.61)			-0.00005 (-0.11)	-0.00001 (-0.10)
Trend (GDP growth rate)						0.02774 (0.20)		0.01875 (0.10)	0.04598 (0.51)
Trend (Inflation)							-0.00139 (-1.02)	-0.00185 (-0.56)	-0.00122 (-1.23)
N	17	17	17	17	17	17	17	17	17
R^2	0.831	0.250	0.009	0.073	0.025	0.002	0.045	0.287	0.896

internationally integrated markets. In this case, an integrated country can grow faster than other countries only when the country has more weights in industries with higher growth opportunities than other countries. Indeed, they show that integrated countries have realized higher growth rates in GDP and investment when they have industrial structure geared toward higher growth opportunities.

In relation to Bekaert, Harvey, Lundblad, and Siegel (2005), the study of Carrieri, Errunza and Sarkissian (2005) is notable because they report the industrial structure has become increasingly aligned across developed markets. These two studies suggest that there might be a convergence in earnings-to-prices ratio among our sample markets because these countries are integrated and the industrial structure across them has become more similar over time.

To address this issue, we first generate two separate series of earnings-to-price ratios, one representing industry effect and the other country effect, for each market and conduct the convergence tests separately with each of the two series. For this purpose, we use 10 broad industry categories corresponding to the level 3 industry classification provided by DataStream.

Following the methodology in Heston and Rouwenhorst (1994), where they decompose stock market returns into returns related to industry and country effects, we decompose earnings-to-price ratio for a market into earnings-to-price ratio related to industry and country effects, respectively. Specifically, we run the following regression to decompose earnings-to-price ratio for industry j in country c (EP_{cj}) into their industry and country components:

$$EP_{cj} = \alpha + \beta_1 * I_1 + \beta_2 * I_2 + \ldots + \beta_{10} * I_{10} + \gamma_1 * C_1 + \gamma_2 * C_2 + \ldots + \gamma_{17} * C_{17} + e_{cj},$$

$$c = 1, 2, \dots, 17;\ j = 1, 2, \dots, 10, \tag{3}$$

where I_j (C_c) is a dummy variable which takes the value of one if earnings-to-price ratio is from the industry j (country c) and zero otherwise. To avoid a muliticollinearity problem, we impose the constraint that the value-weighted sums of the industry and country coefficients equal to zero, respectively. Thus, we estimate the coefficients subject to the constraints that

$$\sum_{j=1}^{10} \omega_j \beta_j = 0, \text{ and}$$
$$\sum_{c=1}^{17} \lambda_c \gamma_c = 0,$$

where ω_j and λ_c are the weights of industry j and country c in the world market portfolio respectively[37]. Since the value-weighted sums of the industry and country coefficients equal to zero respectively, the intercept in the regression can be interpreted as the earnings-to-price ratio on the world market portfolio. The coefficient β_j can be interpreted as the estimated effect of industry j relative to the earnings-to-price ratio on the world market portfolio. Similarly, the coefficient γ_c can be interpreted as the estimated effect of country c relative to the earnings-to-price ratio on the world market portfolio.

To examine the issue of whether the convergence in earnings-to-price ratio is driven by industry effect, we construct two hypothetical series of earnings-to-price ratios for each country – one with industry effect and the other with country effect – using the

---

[37] The world market portfolio here represents the total market capitalization of 17 countries in our sample.

estimated coefficients of the regression. The hypothetical earnings-to-price ratio for country c with industry effect ($EP_{c,ie}$) is defined as follows:

$$EP_{c,ie} = \hat{\alpha} + \sum_{j=1}^{10} \chi_{cj} * \hat{\beta}_j \text{ , c = 1, 2, …, 17,} \tag{4}$$

where χ_{cj} is the proportion of market capitalization of country c in industry j.

On the other hand, the hypothetical earnings-to-price ratio for country c with country effect ($EP_{c,ce}$) is computed as follows:

$$EP_{c,ce} = \hat{\alpha} + \hat{\gamma}_c \text{, c = 1, 2, …, 17.} \tag{5}$$

We separately test the convergence hypothesis with the two decomposed series of earnings-to-price ratios for 17 sample markets.

Table 2.7 reports the test results for the convergence hypothesis with country and industry effects. Table 2.7 provides the test results with country effect. For each distance measure, the coefficient of the time trend variable is negative and significant at least at the 10 percent level. Table 2.7 also provides the test results with industry effect. Again, for each distance measure, the coefficient of the time trend variable is negative and significant at least at the 1 percent level. Thus, we conclude that both country and industry effects account for convergence in earnings-to-price ratios among our sample markets.

However, when we examine the magnitude of each effect on convergence in earnings ratio, country effect dominates industry effect. The intercept and time coefficients related to country effect is about five times larger than those related to industry effect in Table 2.7. Figure 2.7 also clearly shows this dominance of country effect over industry effect. These suggest that although both country and industry effects are responsible for convergence in

Table 2.7. Tests of the Convergence in Earnings-to-Price Ratios with Country and Industry Effects, 1980 – 2004

Country Effect	Intercept	Time	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ statistic)
Cross-Market Average Distance Measure	0.03127	-0.00051	-2.28**	0.431	-3.13***
Cross-Market Median Distance Measure	0.02512	-0.00041	-1.90*	0.329	-3.10***
Cross-Market Standard Deviation	0.04093	-0.00065	-2.30**	0.434	-2.84***
Industry Effect	**Intercept**	**Time**	**t_{HAC} (Time)**	**R^2**	**Unit Root Test for Residuals (τ statistic)**
Cross-Market Average Distance Measure	0.00686	-0.00011	-3.20***	0.453	-3.82***
Cross-Market Median Distance Measure	0.00597	-0.00009	-3.08***	0.416	-3.08***
Cross-Market Standard Deviation	0.00861	-0.00014	-3.18***	0.451	-3.62***

earnings-to-price ratios among our sample markets, the convergence in earnings-to-price ratio documented in the previous section is mainly attributable to country effect.

In this section, we examine which of two effects, industry or country, is the prime driver for the convergence in earnings-to-price ratio. Then, we further examine what could explain the declining country effect Table 2 reports the cross

Convergence in International Accounting Practices or in Economic Factors?

In the previous section, we conclude that the convergence in earnings-to-price ratio among our sample markets is largely attributable to country effect. However, it is not clear why we observe the declining country effect during our sample period. In this section, we will examine whether the declining country effect might be explained mainly by the convergence in international accounting practices as suggested by Land and Lang (2002).

Land and Lang (2002) document convergence in earnings-to-price ratios for a sample firms from Australia, Canada, France, Germany, Japan, the U.K., and the U.S. over the period 1987 – 1999. Since no economic determinant of earnings-to-price ratio shows similar convergence over the period, with some support from the time-series properties of earnings, they conclude that convergence in accounting practices is behind the convergence in international earnings-to-price ratios they document.

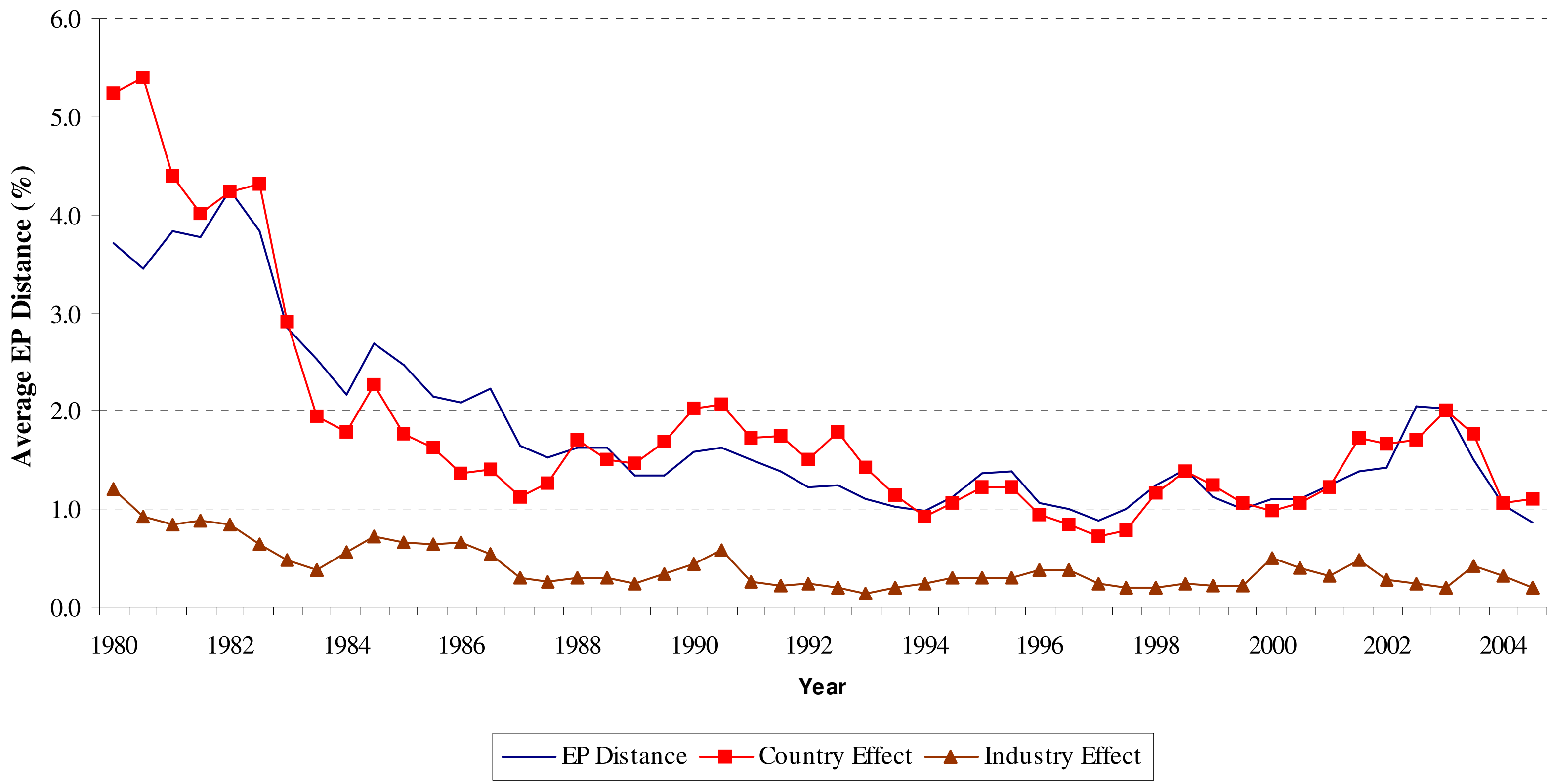

Figure 2.7. Time Trend in the Cross-Market Average of EP Distance Measures for 17 Markets, Country vs. Industry Effects

To examine whether or not convergence in international accounting practices could explain the convergence in earnings-to-price ratio during our whole sample period, we use the following identity, which defines the relationship between earnings-to-price ratio and dividend-yield:

$$PR^*(\text{Earnings/Price}) \equiv (\text{Dividend/Price}) \qquad (6)$$

where PR represents payout ratio. Dividends are actually paid out to shareholders. Thus, if the level of earnings changes due to changes in accounting practices, changes in earnings are not likely to end up with changes in dividends. In turn, if there is little change in dividends and stock prices are computed as discounted future flows of dividends, there is no reason that dividend-yield would change substantially following changes in earnings-to-price ratio due to changes in accounting practices. On the other hand, if the level of earnings changes due to economic forces, changes in earnings probably result in changes of dividends in the end. Thus, in this case, dividend-yield would change as earnings-to-price ratio changes. Based on this reasoning, we introduce dividend-yield distance, which is defined in the same way as earnings-to-price distance, and examine whether or not dividend-yield distance measure also exhibits similar time trend as earnings-to-price distance measure during the sample period. We also introduce payout-ratio distance in a similar way and consider the time trend in payout-ratio distance measure, too.

Table 2.8 reports the test results for convergence in dividend-yields and payout ratios. Table 2.8 provides the test results for convergence in dividend-yields. For each distance measure, the coefficient of the time trend variable is negative and significant at

Table 2.8. Tests of the Convergence in Dividend-Yields and Payout Ratios for 17 Markets, 1980 – 2004

Dividend-Yield	Intercept	Time	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ statistic)
Cross-Market Average Distance Measure	0.01485	-0.00021	-3.64***	0.607	-3.62***
Cross-Market Median Distance Measure	0.01407	-0.00020	-3.17***	0.562	-3.17***
Cross-Market Standard Deviation	0.01797	-0.00025	-3.99***	0.633	-3.05***
Payout Ratio	**Intercept**	**Time**	**t_{HAC} (Time)**	**R^2**	**Unit Root Test for Residuals (τ statistic)**
Cross-Market Average Distance Measure	0.09387	-0.00002	-0.08	0.000	-3.78***
Cross-Market Median Distance Measure	0.07160	0.00019	1.18	0.032	-4.88***
Cross-Market Standard Deviation	0.12154	-0.00001	-0.18	0.002	-3.47***

least at the 1 percent level. Table 2.8 also provides the test results for convergence in payout ratios. Neither of the time coefficients is significant at the conventional level. We can confirm the test results in Figure 2.8 and Figure 2.9. In Figure 2.8, we observe the time trend of dividend-yield distance measure closely follows that of EP distance measure. However, Figure 2.9 shows that the payout-ratio distance measure has neither of upward or downward time trend. Taken together, these results suggest that convergence in earnings-to-price ratio across the sample markets during the whole sample period is mainly due to convergence in economic factors such as growth opportunities or discount rates specific to each country, rather than due to convergence in accounting practices.

Summary and Concluding Remarks

In this paper, we documented a significant convergence in earnings-to-price ratios among 17 markets during the period 1980 - 2004. The speed of convergence, however, varies greatly across individual markets, mainly reflecting the initial distances of individual markets from the international average. We also show that although both country and industry effects account for convergence in earnings-to-price ratios among the sample markets, country effect dominates industry effect in terms of the magnitude of each effect on convergence in earnings-to-price ratio. Thus, we conclude that the convergence in earnings-to-price ratio is mainly attributable to the declining country effect.

Then, we further examined what might explain the declining country effect. Especially, we consider whether or not the declining country effect could be explained by the convergence in international accounting practices as suggested by Land and Lang (2002). We have found (i) that the time trend of dividend-yield distance measure closely

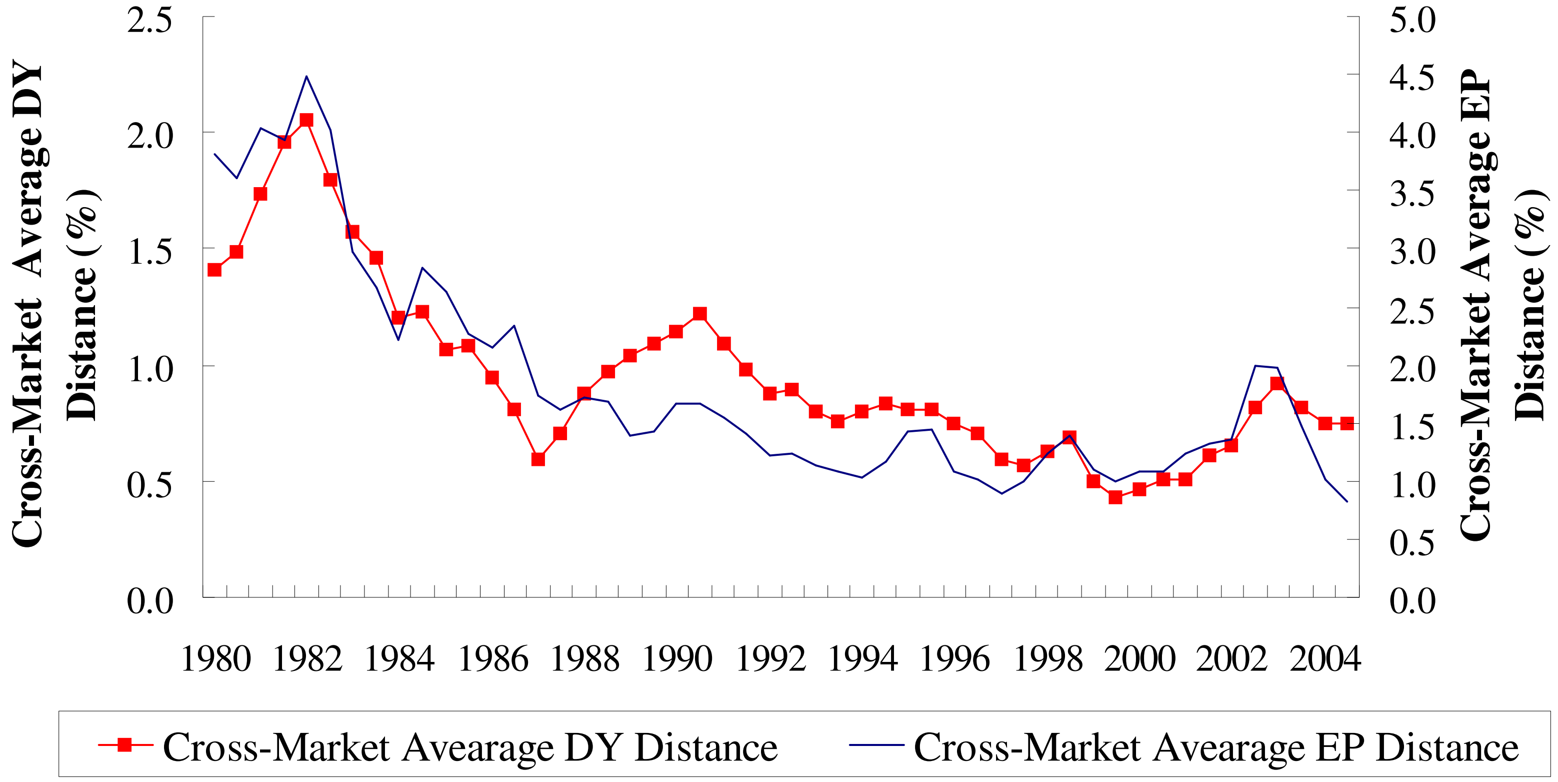

Figure 2.8. Time Trends in the Cross-Market Average of Dividend-Yield Distance Measures

follows that of EP distance measure and (ii) that the payout-ratio distance measure has neither of upward or downward time trend. Over all, these results suggest that convergence in earnings-to-price ratio across the sample markets during the sample period is mainly due to convergence in economic factors such as growth opportunities or discount rates specific to each country, rather than due to convergence in accounting practices.

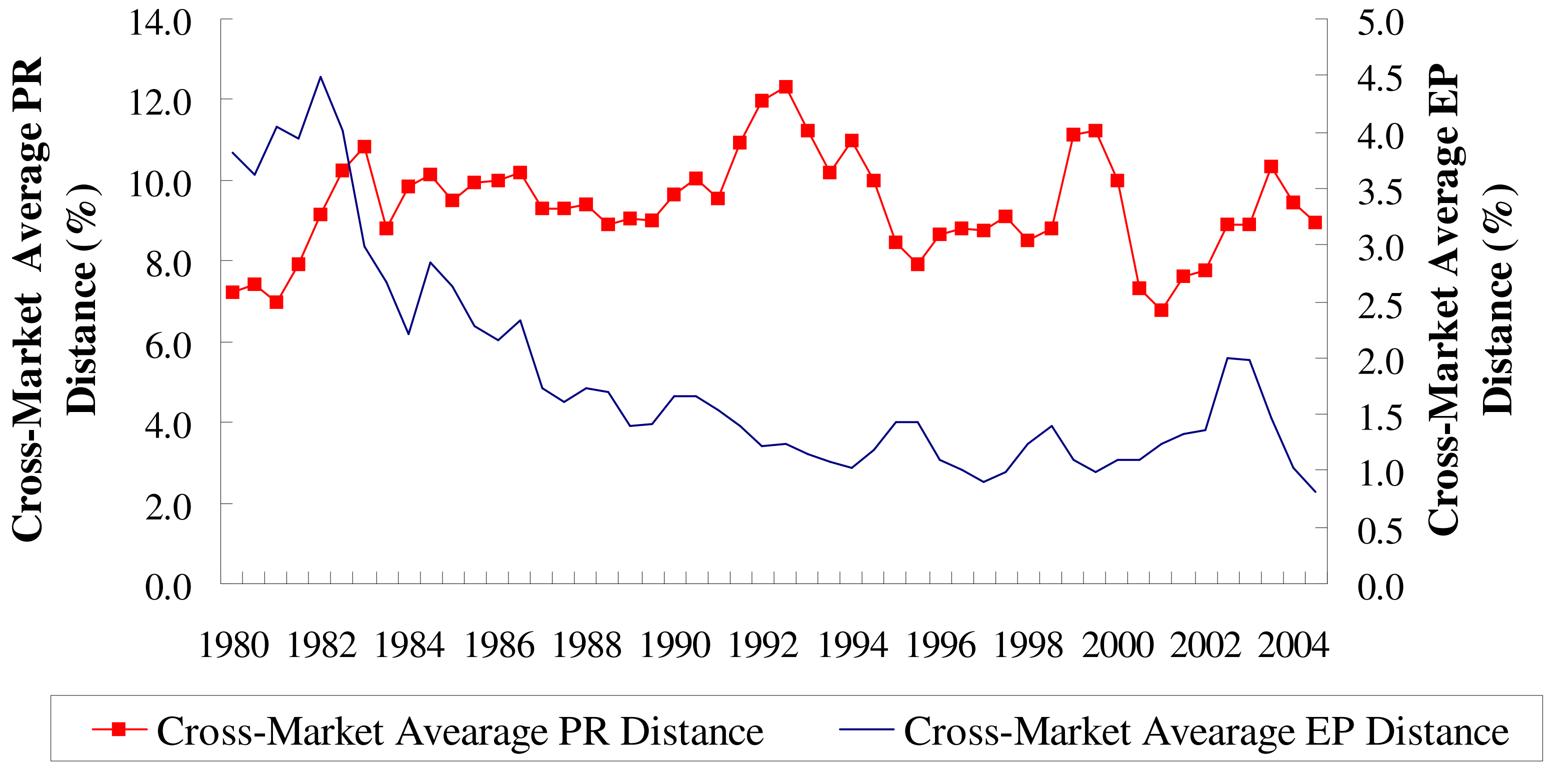

Figure 2.9. Time Trends in the Cross-Market Average of Payout-Ratio Distance Measures

APPENDIX A

PAIRWISE TESTS FOR THE EQUALITY OF TIME TREND PARAMETERS

The following table reports pairwise test results for the equality of time trend parameters (β) for 17 markets. The 17 markets are Australia (AUST), Austria (ASTR), Belgium (BELG), Canada (CNDA), Denmark (DENM), France (FRNC), Germany (GERM), Hong Kong (HGKG), Ireland (IREL), Italy (ITAL), Japan (JPAN), Netherlands (NETH), Singapore (SING), South Africa (SOAF), Switzerland (SWIT), U.K., and U.S. The time trend parameters are obtained from the regressions of the risk-return distance measures as reported in Table 1.3. We use the F statistic proposed by Vogelsang and Franses (2005) for testing the null hypothesis that the two time trend parameters are equal to each other. The superscripts a, b, and c denote rejection of the null hypothesis at the 1 percent, 5 percent, and 10 percent level of significance, respectively. The critical values are 83.96, 41.53, and 20.14 at the 1 percent, 5 percent, and 10 percent level of significance, respectively.

Table A.1. Pairwise Tests for the Equality of Time Trend Parameters Among 17 Individual Developed Markets

	ASTR	BELG	CNDA	DENM	FRNC	GERM	HGKG	IREL	ITAL	JPAN	NETH	SING	SOAF	SWIT	U.K.	U.S.
AUST	24.60[c]	68.16[b]	1.10	0.92	0.82	4.49	102.87[a]	12.32	2.87	85.69[a]	53.99[b]	0.26	2.10	28.80[c]	4.96	28.51[c]
ASTR		47.73[b]	42.55[b]	18.65	12.22	19.73	11.94	0.92	3.34	92.50[a]	61.56[b]	12.98	13.98	31.49[c]	1.05	67.73[b]
BELG			29.34[c]	65.07[b]	316.74[a]	143.91[a]	315.18[a]	194.48[a]	29.16[c]	10.98	10.24	66.66[b]	47.83[b]	68.00[b]	87.02[a]	5.76
CNDA				4.04	0.01	0.75	103.30[a]	13.93	7.75	128.48[a]	49.86[b]	0.06	0.27	7.02	6.21	48.37[b]
DENM					1.67	5.78	118.37[a]	8.95	3.28	128.70[a]	73.94[b]	0.97	2.49	37.55[c]	3.57	59.30[b]
FRNC						1.79	114.87[a]	35.78[c]	3.67	80.46[b]	18.18	0.20	0.38	12.47	14.40	7.74
GERM							149.93[a]	98.92[a]	5.73	103.93[a]	24.40[c]	2.66	0.01	7.37	29.60[c]	5.54
HGKG								44.97[b]	44.93[b]	324.85[a]	203.75[a]	143.58[a]	126.05[a]	189.12[a]	38.47[c]	153.12[a]
IREL									0.55	242.50[a]	89.35[a]	27.64[c]	17.75	67.18[b]	1.00	32.43[c]
ITAL										107.28[a]	27.02[c]	3.02	3.57	13.85	0.16	49.37[b]
JPAN											85.16[a]	81.15[b]	29.31[c]	69.88[b]	136.15[a]	43.13[b]
NETH												19.55	5.52	8.38	37.50[c]	0.12
SING													0.81	9.65	12.38	8.26
SOAF														2.31	9.73	3.53
SWIT															24.78[c]	2.70
U.K.																16.83

APPENDIX B

TIME TRENDS IN THE RISK-RETURN DISTANCE MEASURE AND THE AVERAGE INTERNATIONAL CORRELATION: THE CASE OF JAPAN

For each semi-annual period, the return (risk) distance is computed for Japan. The return distance for Japan is computed as the absolute difference between the mean of weekly returns for Japan and the cross-market average of mean weekly returns for 17 developed markets. Similarly, the risk distance for Japan is computed as the absolute difference between the standard deviation of weekly returns for Japan and the cross-market average of the standard deviations for 17 developed markets. Before the risk-return distance measure is computed, the return (risk) distance is normalized to make similar the impact of each variable on the risk-return distance measure. Euclidean distance is used to measure the risk-return distance. For each semi-annual period, the correlation between weekly returns for Japan and those for each market is calculated. Then, the average correlation of 16 bilateral correlations is computed. U.S dollar stock market index returns are used to compute the distances and parameters.

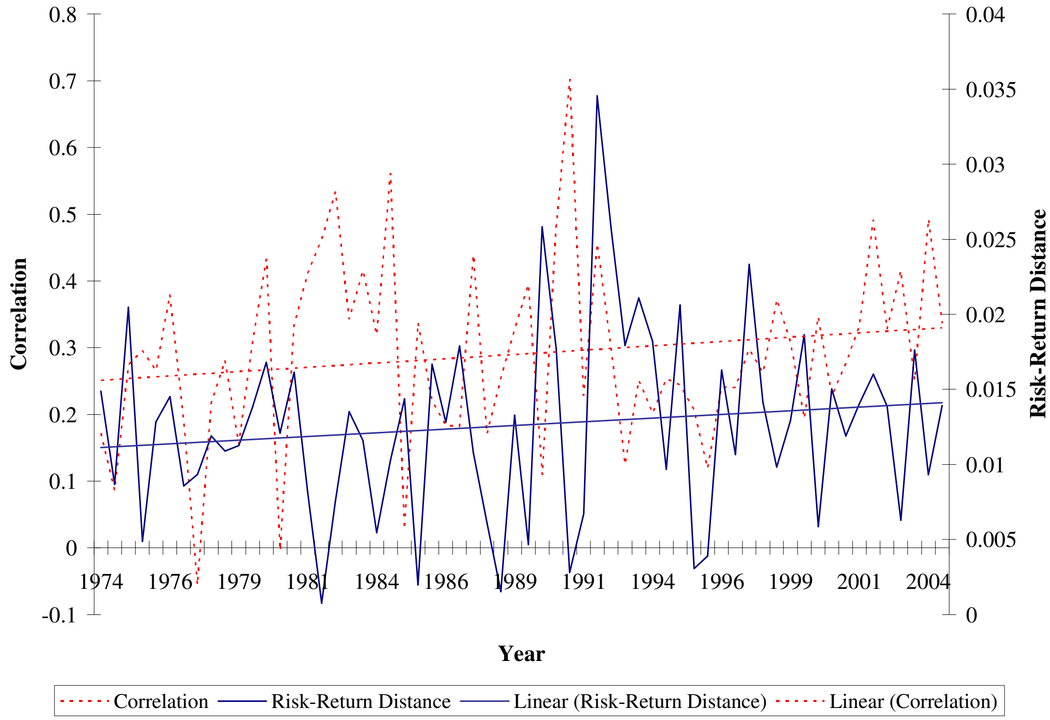

Figure B.1. Time Trends in the Risk-Return Distance Measure and the Average International Correlation: The Case of Japan

APPENDIX C

TIME TRENDS IN THE CROSS-MARKET AVERAGE RISK-RETURN DISTANCE MEASURE AND THE AVERAGE CORRELATION FOR 14 EMERGING MARKETS

For each semi-annual period, the return (risk) distance is computed for each market. The return distance for a market is computed as the absolute difference between the mean of weekly returns for each emerging market and the cross-market average of mean weekly returns for 17 developed markets. Similarly, the risk distance for a market is computed as the absolute difference between the standard deviation of weekly returns for each emerging market and the cross-market average of the standard deviations for 17 developed markets. Before the risk-return distance measure is computed, the return (risk) distance is normalized to make similar the impact of each variable on the risk-return distance measure. The Euclidean distance is used to measure the risk-return distance. The cross-market average risk-return distance for 14 emerging markets is calculated. For each semi-annual period, the correlation between weekly returns for each emerging market and those for each developed market is calculated. Then, the average correlation of all the bilateral correlations is computed. U.S dollar stock market index returns are used to compute the distances and parameters.

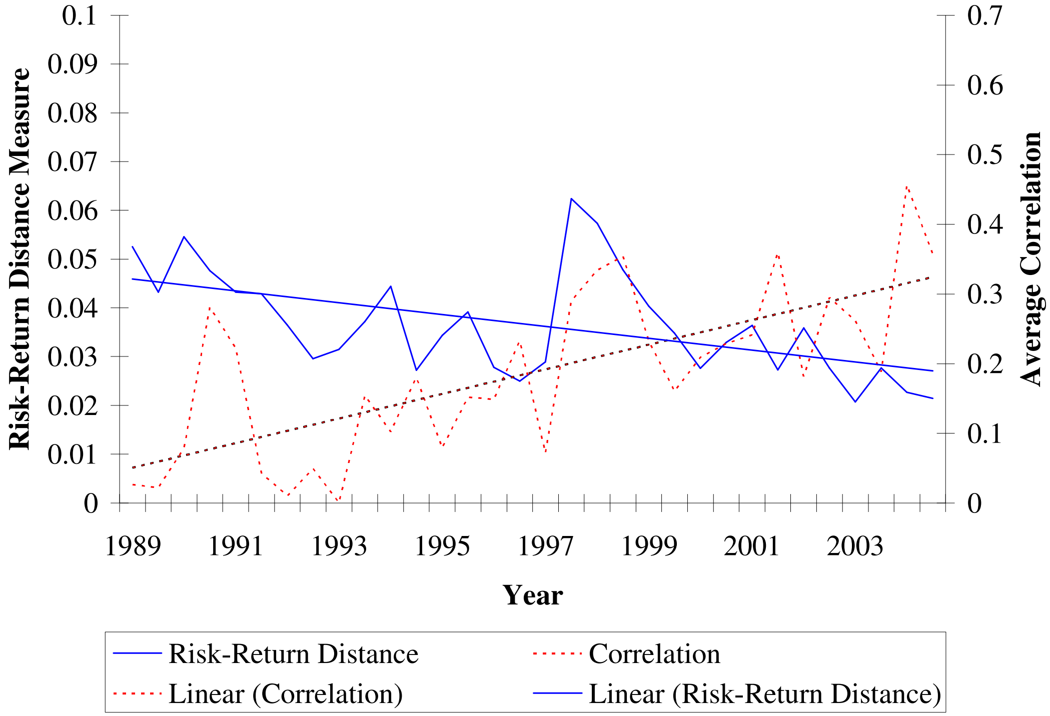

Figure C.1. Time Trends in the Cross-Market Average Risk-Return Distance Measure and the Average Correlation for 14 Emerging Markets

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